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THESIS

AN EXPLORATORY STUDY OF PRE-ADMISSION PREDICTORS OF HARDINESS AND RETENTION FOR UNITED STATES MILITARY ACADEMY CADETS USING REGRESSION MODELING

by

Aris J. Comeaux

June 2013

Thesis Co-Advisors:	Carlos Borges
	Christian Smith
Second Reader:	Bard Mansager

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Aris J. Comeaux
Major, United States Army
B.S., United States Military Academy, 2003

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Author: Aris J. Comeaux

Approved by: Carlos Borges
Thesis Co-Advisor

Christian “Kip” Smith
Thesis Co-Advisor

Bard Mansager
Second Reader

Carlos Borges
Chair, Department of Applied Mathematics

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LIST OF ACRONYMS AND ABBREVIATIONS

AAS	Athletic Activity Score
ADSO	Active Duty Service Obligation
AIC	Akaike's Information Criteria
ANOVA	Analysis of Variance
APS	Academic Program Score
APSC	Cumulative Academic Program Score
ASC	Assessment Steering Committee
AWC	Army War College; Senior Service College
BOLC	Basic Officer Leadership Course
CEER	College Entrance Equivalency Rating
CH2	Hardiness-challenge
CLS	Community Leader Score
CM2	Hardiness-commitment
CO2	Hardiness-control
CPS	Cadet Performance Score
CSI	Character in Sports Index
CV	Cross Validation
FAS	Faculty Appraisal Score
FFM	Five-Factor Model, also known as the "Big Five"
GAM	Generalized Additive Model
GLM	Generalized Linear Models
GMA	General Mental Ability
GWOT	Global War on Terrorism
IAC	Institutional Assessment Committee
LTG	Lieutenant General
MA	Mental Ability
MD	Military Development
MPS	Military Performance Score
MPSC	Cumulative Military Performance Score
MS	Military Science

MSE	Mean Square Error
NPS	Naval Postgraduate School
OIR	Office of Institutional Research
PPS	Physical Program Score
PPSC	Physical Program Score
R	Statistical Computing Software called “[R],” “R:” or “R”
ROTC	Reserve Officer Training Corps
SAT	Scholastic Aptitude Test
SLR	Simple Linear Regression
SOP	Standard Operating Procedures
SSE	Sum of Squares Error
SSTO	Sum of Square Total
SWO	Surface War Officer
USCC	United States Corps of Cadets
USMA	United States Military Academy
USMAPS	United States Military Academy Preparatory School
VIF	Variance Inflation Factor
WAB	Weighted Application Blanks
WCS	Whole Candidate Score

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“Thou art worthy, O Lord, to receive glory and honour and power: for thou hast created all things, and for thy pleasure they are and were created.”

Revelations 4:11

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INTRODUCTION

The United States Military Academy (USMA or West Point) located at West Point, New York, began in 1802 for the purpose of training military officers in leadership and engineering and provide a superb four-year education. After two centuries, West Point's education now focuses on the leader development of cadets in academic, military, and physical domains, all underwritten by adherence to a code of honor (United States Military Academy [USMA], 2013a). Today, USMA carries out its founding fathers' legacy in an unpredictable environment of chaos by preparing young officers for a career in the United States Army.

In an age of performance refinement, USMA, like most premier institutions, must attract agile and adaptable leaders capable of meeting intense demands. This study looks into one of the hidden treasures of performance measurement, hardiness. Hardiness is the pattern of courage and motivation one uses to determine advantageous performance (Maddi, Matthews, Kelly, Villarreal, & White, 2012). Assessed during a cadet's first summer, hardiness accounts for the difference in response to adversity between individuals and may be a tool USMA can use to **select** and **retain** quality personnel.

This thesis explores archived data from three USMA cohorts in order to determine their relationship to hardiness. Secondly, we investigate the relationship of hardiness, and other variables, to retention, both during and after West Point. The goal of this project is to develop a mathematical model that accurately predicts hardiness and retention.

A. RESEARCH OBJECTIVE

In concert with the literature review, the first research objective uses data obtained from the USMA Office of Institutional Research (OIR) to develop a hardiness predictor. Previous research revealed the power of hardiness in predicting performance across multiple domains beyond the Five Factor Model

(FFM). USMA does not allow personality testing as a selection tool. However, perhaps we may discover whether pre-admission information can predict a candidate's hardiness. For this objective, we defined a new success category with hardiness as the outcome and pre-admission "predictor" variables from OIR. The desired output from this research objective is a linear model, useful for predicting future hardiness scores for cadet candidates.

The second research objective explores the relationship between hardiness and retention. Numerous and varied circumstances faced by members of the U.S. military influence an individual's decision to leave or stay in the armed forces. Although we test additional predictors, a rounded investigation may indicate that, regardless of circumstance, hardiness influences retention.

We investigate the retention research objective in two forms. First, graduation status (i.e., whether the cadet graduated or separated from USMA); second, active duty status (whether the U.S. Army retained the USMA graduate beyond his or her[1] initial service obligation or suffered loss).

B. BACKGROUND

1. Service to the Nation—USMA's Mission

A proper mission statement attracts prospects, guides proponents, and provides a means for an organization to measure performance. Since 1925, USMA and Army Regulations documented various mission statements prepared by its leaders to communicate West Point's strategic aim. Past USMA mission statements range from general to specific, but as a whole, center on preparing the Corps of Cadets for service to the nation in the capacity of Army officers.

The current mission of USMA is:

> To educate, train, and inspire the Corps of Cadets so that each graduate is a commissioned leader of character committed to the

[1]Hereafter we use "his" in reference to both genders to limit wordiness

values of Duty, Honor, Country; and prepared for a career of professional excellence and service to the Nation as an officer in the United States Army. (USMA, 2013a)

2. Life as a Cadet

a. Admissions

A West Point cadet is a volunteer member of the United States Corps of Cadets (USCC), selected through a rigorous admissions process, who endures a 47-month experience designed to prepare him to lead in a world of complexity and uncertainty. Cadets comprise of prior-service active duty, Reserve or National Guard soldiers, high school graduates and international military officers between 17 and 22 years of age.

An admission into USMA requires a prospective candidate to exemplify academic, physical and social history prowess. Each appointee must receive a congressional or service-connected nomination granted by the Vice President of the United States, U.S. Senators and Representatives, Delegates of the House of Representatives, or the Secretary of the Army, as well as governors or commissioners of several U.S. territories such as Samoa, Puerto Rico, Guam, Mariana Islands (USMA, 2013b).

b. The United States Corps of Cadets

There are four year groups (YG), freshman through senior class, each broken into four regiments of nine cadet companies with equal numbers of upper and lower classmen in each company. In addition to academic and military requirements, the upperclassmen are responsible for the conduct and training of underclassmen. Plebes (freshmen) spend their entire first year memorizing West Point's history, which include famous quotes from famous graduates, national or military songs, creeds and key definitions. Plebes must also memorize current events and recite knowledge assigned to them by their upper-class chain-of-command.

All cadets participate in an athletic activity—intramurals, club, or corps squad (intercollegiate). While intramural sports remain internal to West Point, club and corps squad teams travel across the country to participate in various NCAA or university contests. Although much of the academic military training occurs during the academic year, West Point dedicates its summers to military training. As one can imagine, a cadet's life is extremely busy, beginning his day as early as 0530 and ending about midnight. Graduation from USMA is the ultimate qualification necessary to become an Army officer, but there are prerequisite qualifications to graduation, one of which is job qualification. Job qualification consists of three categories: admission, graduation and officer.

c. USMA Preparatory School

Cadets who attended the USMA Preparatory School (USMAPS) hold 25 percent of leadership positions within the Corps of Cadets. The chief purpose of USMAPS is to assist in preparing high school graduates and/or enlisted personnel from the active duty, Reserve, or National Guard force for the academic rigors of West Point. Located on the grounds of West Point, USMAPS conducts operations similar to the Academy. Upon successful completion of the one-year program, attendees of USMAPS become fourth-class cadets (freshman) at West Point.

d. Graduation

A cadet is responsible for upholding the cadet honor code and passing his academic, military and physical events prior to graduation. The following excerpt from USMA's academic catalog further defines graduation from the Academy:

> Regulations for the United States Military Academy state that cadets of the First Class who have been found by the Academic Board successfully to have completed the course of instruction, including academic, military, and physical education and training; to have maintained the standards of conduct; and to possess the moral qualities, traits of character and leadership essential for a graduated cadet; shall receive a diploma signed by the

> Superintendent, the Commandant of Cadets, and the Dean of the Academic Board; and shall there upon become a graduate of the United States Military Academy with a degree of Bachelor of Science. (Office of the Dean, 2010)

3. Performance Measurement at USMA

In the land of leadership, performance is *king*. To train and generate high-caliber officers to lead and fight our nation's wars, an accurate measurement of their performance is necessary. In fact, no organization claims legitimacy without first producing a quality product to the customers' satisfaction. Nevertheless, what exactly is effective performance?

Cook (2009) explains that when someone digs deeper into what constitutes effective performance, questions arise concerning the real nature of work or the true purpose of organizations. Cook wondered if we measure success best by counting objects produced or subjectively by informal opinion. Those interested in attending USMA have their performance measured from the moment the Admissions Department receives their applications to the day of their graduation. Before an appointment to USMA is granted, a "range of tests are used to assess a range of attributes" (Cook, 2009).

4. Life as an Army Officer

After a successful completion of the academic, physical and military requirements, USMA commissions its senior class into the United States Army as Second Lieutenants. USMA expects their commissioned leaders to develop a "capacity to lead."

a. Officer Qualifications

Before leaving USMA, the senior ("firstie") class assesses into one of the seventeen Army career fields ("branches"). Order of merit (e.g., class rank) determines branch choice–a firstie may choose any branch for which he meets the basic requirements. For example, seniors wishing to select the aviation branch must pass a comprehensive flight physical, and the Army flight aptitude selection test. There are similar requirements for cadets wishing to select the medical service corps as their branch in order to become doctors or nurses.

A litmus test of USMA's effectiveness as an institution is the graduate's ability to achieve various officer qualifications after leaving the Academy. The Basic Officer Leadership Course (BOLC), for example, certifies a recent graduate to serve in his chosen branch at the Platoon Leader level; all lieutenants must pass BOLC before departing to their first duty station. The Captains Career Course, and Command and General Staff College (Intermediate Level Education) prepare a Captain and Major, respectively, to lead and serve in various staff positions. For lieutenant colonels and above, the Senior Service College (i.e., Army War College) provide courses to prepare them to assume strategic leadership responsibilities in military or national security organizations (Human Resources Command [HRC], 2013).

A qualified officer not only facilitates the Army mission, but also remains competitive in his career category, making promotion inevitable. However, meeting the basic qualifications is an expectation rather than an exception. Thus, exemplary evaluations from superiors play a significant role in identifying qualified officers for promotion.

C. REVIEW OF LITERATURE

All academic organizations have the *success* of their personnel as their chief goal. West Point is no different. The undeniable goal of the mission statement is "to produce agile and adaptable officers who are developed intellectually possess the knowledge of 'how to think' rather than simply 'what to think'" (USMA, 2009). USMA, as an academic institution, emphasizes intelligence and is convinced of its importance to leadership. However, there cannot be success without a determination to perform well.

1. Human Performance

In identifying those who possess the commitment to "supporting and defending the Constitution" (United States Army [USA], 1999), the word *performance* comes to mind. Yet, how do we measure performance appropriately and in harmony with USMA's goals? In *Human Performance: Cognition, Stress and Individual Differences* (Human Performance), Matthews et al. (2000) mention the significance of valid performance measurements. Validity exists in several forms. First, *Criterion Validity* refers to "the ability of a test or measure to predict some other intrinsically interesting measure". Another way of saying this is, do the performance measures relate to the organization's goals?

Secondly, *Construct Validity* considers whether the performance measure assesses a meaningful theoretical construct (Matthews et al., 2000). For example, does the performance measure (e.g., Intelligence Quotient Test) relate to the theory behind it (true Intelligence)? Construct Validity is interesting because it presupposes the theory is well developed and understood. For instance, measuring intelligence assumes we know what "true intelligence" is and assumes we can accurately measure it (Carter, 1991).

A related concept is *reliability*. It refers to a performance measures' ability to yield similar outcomes over time. Matthews et al., say, "If measurement of either the ability or criterion is unreliable, then high correlations between skill and other measures cannot be expected..." (Matthews et al., 2000).

The authors of *Human Performance…* offer two approaches to measuring performance in the context of personnel selection. The first approach uses general mental ability assessments (GMA), while the second approach uses a tailored test based on job demand. GMA tests a broad range of abilities and is increasingly valid when assessing intelligence-demanding jobs. GMA tests, when used as the primary instrument, are misleading when the organization requires personnel to use physical skill, ethical decision-making, a personality-centered skill, or a combination of the previous with cognitive skill. Performance is a broad concept that must be described and designed for each organization (Carter, 1991). Furthermore, when speaking of cognitive abilities, Matthews et al. mention, "for accurate prediction of performance, knowledge of more specific abilities is also necessary…." Thus, even for intelligence measurement, multidimensional testing is necessary to measure a person's true performance. It is easy to see how the multidimensional testing becomes a series of tailored tests, with the benefits being shared confidence, among selectee and organization, in the expected outcome(s).

Neil Carter took this a step further and defined outputs and outcomes in his 1991 article *Learning to Measure Performance: The Use of Indicators in Organizations*. Carter (1991) asserted that outputs eclipsed the goal of quality and customer satisfaction, and he used a financial example to communicate his point:

> To assess the meaning of profits (or of alternative key indicators) involves forming a judgment on the performance not just of the firm in question but of its competitors, as well as strategic judgments about the long-term effects of current pricing and investment decisions. (Carter, 1991)

Although the present work will not discuss financial aspects, the spirit of Carter's claim is in finding the right indicators to measure true (and lasting) performance. Alas, the ability to measure outcomes (e.g., qualified and agile-minded U.S. Army officers) versus mere outputs (e.g., graduates), irrespective of quality, is difficult. Performance measurement must begin with an organizations' definition of success, goals, and outcomes, and then work backwards from there (Carter, 1991).

Another recent study that drew conclusions on the indicators of USMA cadet performance is a Fielding Graduate University doctoral dissertation by Jennifer Clark (2007). Clark identified three performance goals for USMA cadets. In the opening paragraph of her dissertation, two goals were identified, namely, the "ultimate success" for a USMA cadet is graduation from the academy and a productive career as a commissioned officer of the United States Army."

The third goal, in concert with her research objective, was academic performance as measured by cumulative grade point average (GPA) (Clark, 2007).

In her dissertation, Clark purposed to identify the relationship between sleep quality and sleep characteristics, to include a Morningness-Eveningness characteristic, and personality factors as described by the Five Factor Model (FFM) to determine their effect on one's academic performance at USMA (Clark, 2007). The FFM asserts that (the personality factors) Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism best describe an individual's personality (Costa & McCrae, 2013; McCrae & John, 1992). A discreet device called an Actigraphy Watch, worn on the wrist, measured sleep quality. Freshmen cadets who participated in the study wore an Actigraphy watch at various times during the year.

Morningness (Horne & Ostberg, 1977) is a character trait used to describe as one "predisposed to waking up earlier rather than later and to going to bed earlier rather than later" (Clark, 2007). The opposite is true of Eveningness. Clark hypothesized that "…given the characteristics of evening and morning types and the effect of lack of sleep on performance…daytime sleepiness can lead to decreased attention, concentration, and poorer academic performance." Secondly, Clark hypothesized "…personality factors may ameliorate some negative effects of sleep habits, sleep quality, or sleep quantity in order to enable one to successfully meet the mental, physical, and emotional challenges of their environment" (Clark, 2007). Clark found Morningness positively related to FFM Conscientiousness, and as a byproduct of her research, Conscientiousness positively related to academic performance, regardless of sleep quality attained. However, Clark's research concluded personality traits, sleep quality, and Morningness-Eveningness were unrelated to better academic performance.

Coincidentally, Clark's literature review noted findings she later confirmed in her own study. Clark cited researchers (Trockel, Barnes, & Egget, 2000) who found "examples of individuals who averaged less than five hours of sleep per night and yet did not have low GPAs, indicating that there may be other mitigating or moderating factors in place which affect the relationship between sleep and GPA" (Clark, 2007). Additionally, Clark cites previous research (Chamorro-Premuzic & Furnham, 2003) showing personality as mildly important in predicting academic success; FFM facets account for 15-17 percent of the variance in academic success, thus, revealing the possibility for other domains to account for the remaining variance. Although Clark originally hypothesized sleep quality and quantity as the culprit of performance variance, her findings proved contradictory. Thus, we explore a different characteristic in this thesis, namely, hardiness. In the next section, we see how crucial hardiness is to performance.

2. Stress, Personality and Performance

What accounts for how one cadet overcomes adversity while others flounder and fail? Bartone, Snook, and Tremble (2002) published an article that considered the USMA admission process in order to identify the pre-admission attributes that best contribute to leader performance at West Point. In *Cognitive and Personality Predictors of Performance in West Point Cadets*, Bartone et al. (2002) used hierarchical multiple regression procedures to find pre-admission variables that predicted military development (MD) grades of upperclassmen three to four years later. The MD grade measured the most enduring and desired quality of West-Pointers and U.S. Army officers leadership performance.

Cadets received the MD grade from an immediate cadet supervisor and their Army officer supervisor. The supervisors generated subjective summations based on 12 military-centered dimensions: duty motivation, military bearing, teamwork, influencing others, consideration for others, professional ethics, planning and organizing, delegating, supervising, developing subordinates, decision-making, and oral and written communication. For cognitive predictors, Bartone et al., assessed entering freshman (termed "new cadets") during their first USMA experience, a summer military training program deemed "Beast Barracks," in the following types of batteries: Spatial Judgment, Logical reasoning, Social Judgment and Problem Solving. Additionally, the College

Entrance Equivalency Rating (CEER), collected as part of the admissions process was used (CEER is computed by combining a weighted average of high school class rank and pre-college Scholastic Aptitude Test scores).

Lastly, FFM analog indicators showed CEER as the main predictor of leader performance three to four years later (Bartone, Snook, & Tremble Jr., 2002). This is surprising since CEER is academically oriented while the MD grades, based on the twelve dimensions, appear relatively non-academic. The CEER–MD grade connection reveals one or two possibilities. Bartone et al. (2002) suggest that either supervisors/raters ascertain the intelligence of rated cadets before judging military performance or CEER is really measuring something else, namely, underlying personality characteristics positively related to military performance.

According to Bartone et al. (2002), overall variance in leader performance was “modest, leaving much unexplained…statistical significance among predictors does not amount to variance (R^2=.05) being accounted for.”

Digman (1990) details the development of the FFM, claiming that five dimensions adequately describe normal personality. Digman chronicled the evolution of the FFM and documented studies supporting the robustness of the FFM. Yet, Digman admitted issues with defining the personality dimensions. He argued that the FFM, at the very least, provided a broad standard and a “surprisingly general theoretical structure” for measured personality (Digman, 1990). Digman ended the article with the following statement:

> The *why* of personality is something else. If much of personality is genetically determined, if adult personality is quite stable, and if shared environment accounts for little variability in personality, what is responsible for the remaining variance? Perhaps it is here that the idiographic (i.e., idiosyncratic) study of the individual has its place. Or perhaps we shall have to study personality with far greater care and with much closer attention to the specifics of development and change than we have employed thus far. (Digman, 1990)

Previous research inspired further exploration of personality dimensions. Our hope is to find a more descriptive factor to help us study the individual. That brings us to the hardiness.

3. Hardiness

Hardiness is “a pattern of attitudes and skills that provides the existential form of courage and motivation needed to learn from stressful circumstances in order to determine what will be the most effective performance” (Maddi, Matthews, Kelly, Villarreal, & White, 2012). According to Maddi et al., hardiness is composed of three areas applicable to a variety (both physical and mental) of situations and occupations.

The first area is general *commitment* (versus alienation) to work and life. A person high in hardiness-commitment remains vigorously engaged or involved with others and activities. The second area is high sense of *control* (versus powerlessness) which urges a person to persevere so that his efforts influence events and outcomes. The last area of hardiness is the ability to assess difficult and trying situations and use them as a *challenge* to grow (versus a threat to avoid). An individual high in hardiness-challenge is open to variety and changes, which are seen as an opportunity to further develop through what is learned (Maddi et al., 2012).

Bartone, Eid, Johnsen, Laberg, and Snook (2009) summarized a similar study on personality factors as indicators of performance. The study evaluated the influence of psychological hardiness, social judgment, and FFM personality dimensions on leader performance in USMA cadets. The study used the following factors as potential predictors of leader performance: gender, CEER, social judgment, FFM-factors and hardiness. The Bartone et al. (2009) study measured leader performance similar to Bartone et al. (2002); however, researchers collected MD grades from two different periods—summer and academic year. The first measurement averaged all three MD grades received during the first three summers at USMA, while the second measurement averaged all MD grades from the four-year academic periods. Lastly, a combined leader performance measure averaged the two previous MD outcomes (summer and academic year). After controlling general intellectual abilities, hierarchical regression results showed FFM extroversion, hardiness, and a trend for social judgment predict leader performance in the summer field-training environment. During the academic period, leader performance predicted mental abilities (CEER), FFM conscientiousness, and hardiness, with a trend for social judgment (Bartone, Eid, Johnsen, Laberg, & Snook, 2009).

In addition, Bartone et al. (2009) found evidence of a relationship between hardiness and FFM's extroversion and conscientiousness. Therefore, FFM factors in combination with hardiness present significant results, with hardiness being the strongest predictor. Additionally, the Bartone et al. (2002) study used FFM analog indicators as potential predictors of leader performance, finding limited correlation between dependent variable and response. In fact, three of the five FFM factors exhibited multicollinearity, while the remaining two showed no correlation.

These findings suggest that hardiness may capture much of the performance variance we are interested in and aid in identifying the multicollinearity concerns among FFM factors. The FFM is unique in that it developed the better part of a half-century into the "unified framework" for understanding normal personality that exists today (Bartone et al., 2009). For now, the FFM uses the five factors of openness, conscientiousness, extraversion, agreeableness, and neuroticism; however, a growing collection of literature states that FFM "may not fully represent all of the personality-based differences potentially impacted on leadership and job performance" (Bartone et al., 2009). In fact, Block (1995) and Hough (1992), both cited by Bartone et al. (2009), echo criticisms of the FFM, addressing the shortfalls, namely breadth, of the five factors to predict performance with the desired specificity. Two additional articles, Duckworth, Matthews, Kelly & Peterson (2007) and Bartone, Kelly, and Matthews (2013), take a similar approach, commenting not only on the generality of the five factors, but also citing insignificant correlations with leader performance as a reason to disregard the FFM.

The aforementioned studies promote hardiness as a relevant predictor of leader performance. Additional results from Bartone et al., (2009) follow:

- Hardiness uncorrelated with gender or CEER.
- Gender was not deterministic of summer leadership performance.
- CEER (mental ability) was not deterministic of summer leadership performance.
- CEER is a significant predictor of academic leader performance.
- Hardiness is the most significant predictor in both training contexts.
- CEER negatively relates to FFM neuroticism and extroversion.
- CEER positively relates to FFM agreeableness and conscientiousness.

These results appear to reveal that FFM is useful in academic contexts at associating a single factor with a performance outcome. However, when the environmental context shifts, that predictor may not be significant. For instance, Conscientiousness does well in predicting outcomes within academic context, but not necessarily in the summer (training) context.

Hardiness, on the other hand, is detectable, regardless of the context or situation, provided there is adversity to overcome. Perhaps the hardy individual is blind to context; his hardiness shines through regardless. Bartone et al. state, “hardiness emerges in this study as the strongest personality predictor of leader performance, and the only personality factor predicting leader performance across the two different contexts” (Bartone et al., 2009).

Interestingly, hardiness is a variable already collected by USMA on its cadets during their first summer. Although few (West Point) entities analyze hardiness data, it is stored in a database managed by OIR. On the genesis of hardiness testing at West Point, USMA Professor of Engineering Psychology, Michael D. Matthews wrote:

> The genesis of hardiness research here traces back to research conducted by COL Paul Bartone. Paul did his doctoral dissertation at the University of Chicago, on the topic of hardiness, and mentored by the scientist who invented the concept, Dr. Salvatore Maddi. Prior to joining the West Point faculty in the late 1990s, Paul had already conducted hardiness research on other military populations. The decision to conduct hardiness research here was simply to extend existing hardiness research to this particular setting/ venue. Since Paul departed in 2003, Dr. Dennis Kelly and I have continued this line of research. To clarify a bit more, USMA did not have a role in the genesis of this research. It was scholar-driven, not institution driven. (Matthews, 2013)

Kelly and Matthews conducted a recent study (2012) with hardiness creator Dr. Salvatore Maddi entitled *The Role of Hardiness and Grit in Predicting Performance and Retention of USMA Cadets*. The research resolved to identify the relationship between hardiness, grit[2], performance, and retention of plebes (freshmen cadets) "above and beyond" the Whole Candidate Score (WCS). The WCS, when used in combination with other pre-admission data, is the primary predictor for West Point cadet academic, military, and physical performance (Maddi, Matthews, Kelly, White, & Villarreal, 2012). Maddi et al. defined WCS in the following way:

> [WCS is] a weighted composite score that measures high school academic performance (e.g., Grade Point Average (GPA), high school rank, and SAT scores), leadership potential (involvement in leadership roles within extracurricular activities—that is, school officers, scouting, debate, and faculty appraisals) and physical fitness (performance on standardized physical exercises). (Maddi et al., 2012)

A dichotomous variable (1= retained beyond year one, 0= separated within year one) characterized retention. The cadet performance score (CPS) measured first year performance. Similar to WCS, the CPS is a weighted composite measure of performance across three USMA developmental

[2] Duckworth et al. (2007) defines grit as "perseverance and passion for long-term goals…grit entails working strenuously toward challenges, maintaining effort and interest over years despite failure, adversity, and plateaus in progress."

programs—academic, military, physical (United States Corps of Cadets [USCC], 2012). Regression analyses revealed the following results:

- WCS, hardiness, and grit predict first year (cadet) retention; yet, grit proved the most important predictor. Retained cadets possessed higher grit scores.
- WCS, grit, and hardiness associate with CPS; yet, WCS and hardiness scores uniquely predict CPS scores. Moreover, hardiness predicted unique variability in CPS after controlling WCS scores.

Maddi et al., (2012) broke from established methods (e.g., FFM, Mental Ability) of measuring performance when they explored hardiness; however, a self-assessed hardy person may be a poor and lazy leader, one who neither ventures into leadership roles nor seeks challenges to overcome. Similarly, an individual strong in academics who is high in hardiness-challenge may perform worse in (military) leadership tasks (Bartone, Kelly, & Matthews, 2013) because he takes unnecessary risks. Therefore, like any personality measure, haphazard application of the hardiness score may lead to erroneous results.

Bartone et al., (2013) evaluated whether psychological hardiness at entry to West Point predicts leader performance and adaptability over time. The authors defined hardiness (psychological) as a "constellation of personality qualities found to characterize people who remain healthy and continue to perform well under a range of stressful conditions". New to this discussion is the concept of *adaptability*.

USMA defines *adaptability* as "a cadet's ability to anticipate and respond effectively to the demands of multiple competing responsibilities" (USMA, 2009). Again, USMA's leader development goal is to produce officers who are agile, adaptable and intellectually developed—possess knowledge of 'how to think' rather than simply 'what to think'" (USMA, 2009). Bartone et al. (2013) seem to agree adaptability is "effective change or adjustment in response to changing conditions." The authors (Bartone et al., 2013) expressed support for an adaptability scale developed by Pulakos, Arad, Donovan and Plamondon (2000).

The adaptability scale measures eight dimensions of adaptability performance—Bartone et al. (2013) created a ten-item survey consistent with that of Pulakos et al. (2000).

The *adaptability* study also used scholastic aptitude test (SAT) scores and WCS as potential predictors of performance. Specifically, criterion variables were cumulative military performance score (MPS), self-rated adaptability, and supervisor-rated adaptability. MPS, captured during the senior year, provided an index of traditional military performance. Adaptability measures, on the other hand, were collected three years after graduation, using the adaptability scale (self-rated) and a survey (supervisor-rated) administered by West Point's institutional assessment committee (IAC). The IAC is USMA's feedback mechanism, validating the achievement of its educational program goals three years after each class graduated by survey or interview from the graduates' superior/commanding officer (USMA, 2009). Findings from Bartone et al., (2013) are as follows:

- SAT and hardiness-challenge are negative predictors of leader performance
- The pattern suggests that the more intelligent (SAT score) and adventurous (hardiness-challenge) cadets do not perform as well as the less intelligent in the conventional military and leadership tasks in the West Point environment.
- SAT scores do not relate to MPS or Adaptability.
- WCS predicts USMA leader performance, but not adaptability post-USMA.
- The stable and highly regulated environment of West Point stands in contrast to the uncertain real-world operational environment.
- Hardiness (commitment, control) predicts leader performance at USMA, self-rated adaptability and supervisor-rated adaptability after graduation.
- Psychological hardiness (commitment and control facets) measured as academy freshmen predict leader adaptability in officers for seven years or more after graduation.

- Hardiness-commitment correlated with USMA military performance, and with later self-ratings of adaptability, but not with commander ratings.
- Hardiness-control showed a significant correlation with military performance at West Point, and correlates with self and commander ratings of adaptability.

Lastly, Bartone et al., (2013) concluded “hardiness…and the facets of commitment, control and challenge appear to be distinct from FFM personality dimensions...it is conceivable that some important personality characteristics are not captured by the FFM…” However, the authors also acknowledged that the hardiness facets may operate somewhat independently; hence, it is worth looking at the facets individually, alongside the total hardiness score.

Table 1 (located in section I.*D*), contains a summary of the literature review.

4. Personnel Selection

Cook (2009) stresses the importance of people in any organization. So much is the value of people that organizations spend large amounts of time and money finding (e.g., advertising or recruiting) the right person for the job. Cook asserts, “Employees vary greatly in value, so selection matters…selection uses a range of tests to assess a range of attributes”. Nevertheless, before a selection instrument is used, the organization’s leaders must agree on suitability criterion for performance outcomes. Doing so will set a standard and, like a net, “catch” qualified personnel. Remarkably, exploring the performance outcome criterion generated questions about the real nature of work or the true purpose of the organization (Cook, 2009).

Cook developed a personnel selection model for a British university. We briefly considered this model before we looked at USMA’s personnel selection system. Figure 1 shows a modified version of Cook’s model.

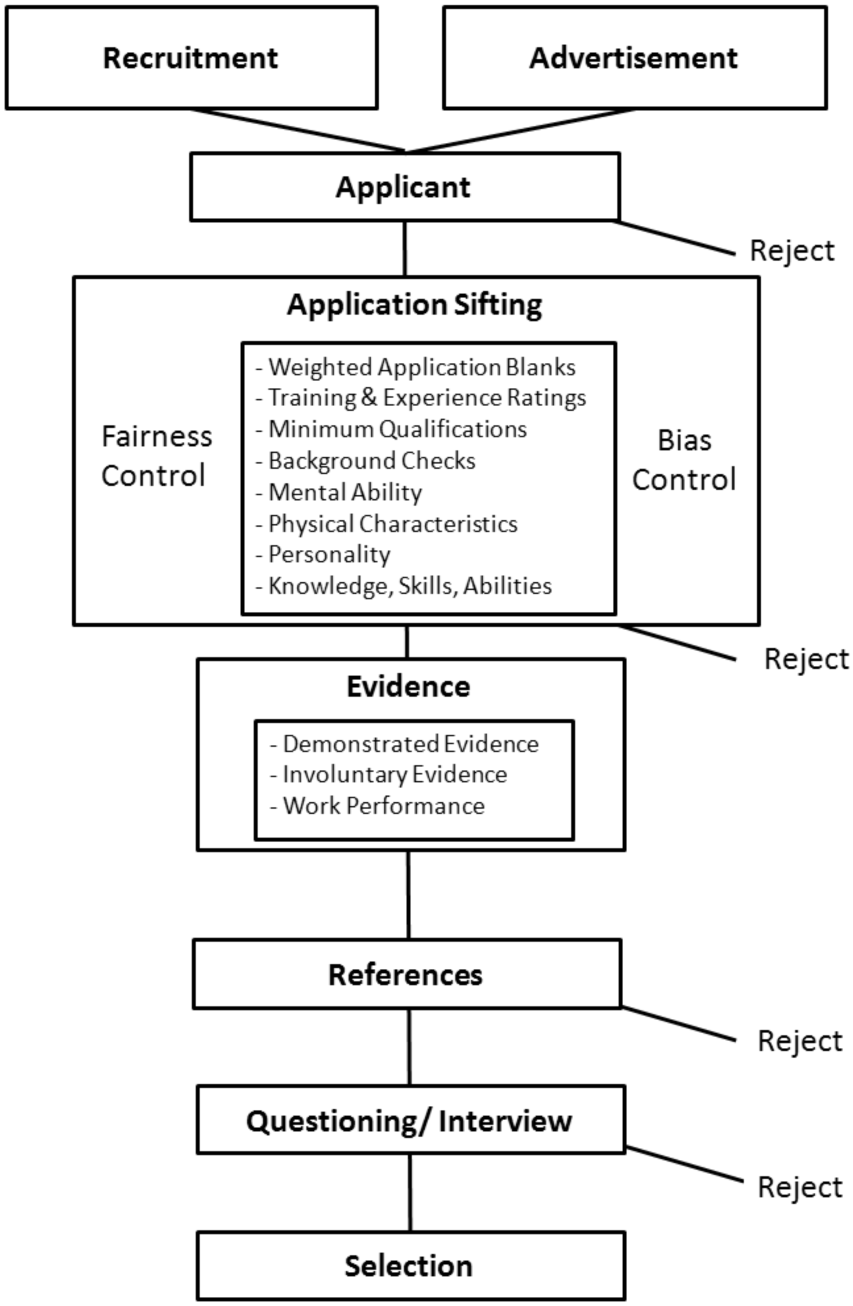

Figure 1. Personnel Selection Model (After Cook, 2009)

In order to spare the reader an extensive explanation of Cook's model, we insert notes of clarification to assist in understanding USMA's selection model.

a. Applicant

Before an applicant begins the application process, he must meet all basic requirements (e.g., minimum educational experience, citizenship).

b. Application

The application stage is a screening process. The self-report application elements (mental ability, training and experience ratings, background, personality, etc.) convert into quantified measures by using weighted application blanks (WAB). WABs are useful as predictors of performance when employed correctly (Cook, 2009).

c. Evidence of Abilities

The evidence stage searches for concrete proof of an applicant's true knowledge, skills and abilities. Demonstrated ability, vice self-reported ability, manifests itself through testing, simulations, or exercises. The test or exercise helps develop an index of the applicant's work performance. However, the organization must agree on the definition of "successful" performance. Cook (2009) identified several questions about the true nature of work and purpose of the organization while exploring performance:

- Is success measured best by counting objects produced or by subjective opinion?
- Who decides whether work is successful?
- Does the organization and its customers agree?

The researcher adds:

- Is the selection instrument correlated with job tasks?

The remaining stages of the modified model (References, Questioning/Interview) validate the written application through personal interaction. Both stages, when credible and convincing, will increase the strength of an application.

5. Use of Mental Ability Testing in Personnel Selection

The validity of Mental Ability (MA) tests is an important portion of individual performance and increases with job complexity (Cook, 2009). The universal assumption here is complex jobs require high mental faculties. However, USMA does not expect its cadets to know every answer to every single problem; rather, USMA expects its leaders to be tough-minded thinkers capable of knowing where to find elusive answers. It suffices to say, MA is not a panacea. Recall the recent studies showing intelligence as not indicative of Adaptability or Summer Field Training performance (Bartone et al., 2009; Bartone et al., 2013). Cook (2009) mentioned a feasible use for MA testing, that MA tests predict training success well on timed, multiple-choice exams. Conversely, MA is not good for predicting personality, measuring leadership, or work quality.denote

MA testing has become unpopular and controversial due to gender, racial bias and varying validity. In fact, many American employers abandoned MA testing after passage of the 1964 Civil Rights Act, yet many adverse impacts still have not been resolved (Cook, 2009). The job description of the U.S. Army officer provides evidence as to why USMA will not use MA as a sole selection tool. U.S. Army officers are multi-dimensional and expected to possess more than intellectual prowess. The U.S. Army's "Project A" found MA somewhat positively related to work performance. Project A showed the following correlations[3] between work performance and three "motivational aspects of work": effort and leadership (r =.31), personal discipline (r =.16), and physical fitness & military bearing (r =.20) (Cook, 2009; McHenry, Hough, & Toquam, Hanson, 1990). Cook (2009) continued, "personality tests, structured interviews, and work samples are worth being used alongside MA to offer incremental validity."

[3] We mention correlation several times in this thesis and represent it with the letter "*r.*"

USMA followed a similar approach by using a myriad of assessments alongside MA. For instance, although personality testing does not occur prior to selection, USMA can no doubt identify a candidate's personality framework from information (e.g., biographical, social) collected prior to admission. An individual's demographics, membership to various organizations, letters of recommendation and educational experience, among others, play an important role in helping USMA identify future leaders of the Nation. In the next section, we discuss USMA's personnel selection model and admissions process.

6. Personnel Selection at USMA

USMA's objective and quantitative selection process essentially reduces applicants to a series of numbers. As impersonal as it sounds, a quantitative process is warranted due to the large number of applicants and, more importantly, because of predictive capability. Many studies (Dawes, 1971, 1974, 1977 & 1979) document quantitative means (e.g., regression equations) as superior to subjective assessments (e.g., admissions committee member ratings). USMA may inspire over 15,000 high school juniors to open a candidate file (USMA, 2013c). This *every-candidate-a-number* concept allows for objective measurement against USMA standards and comparison among individuals. Generally, candidates with higher numbers are more qualified; however, this is not always the case. To prove this point, a member of USMA admissions department wrote, "The subjectivity only comes in if we request WCS bonuses[4] for a candidate's file or during the nomination process (congressional districts can use the principal nomination process that allows them to choose their vacancy winner regardless of their WCS)" (Unger, 2013). Of the 15,000 candidates, over 4,000 received congressional nominations. Yet, USMA reduced their pool of interested applicants to approximately 1200, less than or equal to

[4] In the event that a particular candidate's WCS insufficiently captures his true potential, USMA admissions may award WCS bonus points.

the number of appointments allowed by congress. A nominated candidate must patiently wait for acceptance status while his entire file undergoes meticulous scrutiny.

This thesis centers on the *whole candidate* concept and scrutinizes past, present, and potential performance in USMA's top three areas: academic ability (60 percent), leadership potential (30 percent), and overall fitness (10 percent) (USMA, 2013c). Previous research revealed the connection between the three areas, performance and retention (graduation versus separation). Therefore, USMA maintained what they call "risk levels and required checks," a list of cut-off scores that must be met for each candidate for each category. For example, an SAT-Verbal score < 560, CEER < 520, or WCS < 5200, alerts the admissions department to the potential risk of admitting a candidate. On the other hand, a community leadership score (CLS) > 650 or CEER > 650 identifies a candidate as a *scholar* or *leader*, respectively (USMA, circa 1996). An explanation of the tool and equations West Point used to quantify candidates is located in Appendix B.

7. Performance Measurement at USMA

A key to the success of any organization is holistic adherence to its standard operating procedures (SOP). The SOP serves as a guiding light to employees, often showing them how or when their mission is complete. The USMA SOP documents command and administration topics for the United States Corps of Cadets (USCC), to include obligations, definitions, standards, authorizations and privileges. It covers topics such as military courtesy, uniform wear and appearance, behavioral conduct, accountability, academic policies, etc., (United States Corps of Cadets ["USCC"], 2012). Before graduation, a cadet must meet the many expectations outlined in USCC's SOP.

In particular, and critical to the topic of performance measurement, a cadet must fulfill the academic, military, and physical program standards prior to graduation. Subordinate to the USCC SOP are each programs' guidebook, deemed the Redbook (academic program), Greenbook (military program), and Whitebook (physical program). Each program yields an associated program score at the completion of training (academic program score–APS, military program score–MPS, and physical program score–PPS). These scores allow comparisons between cadets and, when combined, create the CPS. USMA assigned the following weights to the CPS elements:

CPS = .55(APS) + .30(MPS) + .15(PPS) (Special Assistant to the Commandant for Stategic Planning [Planning], 2010).

Earlier, we saw similar weights assigned to academic, leadership, and fitness domains of the Whole Candidate Concept. For context, we mentioned several definitions.

a. Academic Program Score

Performance in courses within the academic program comprises the APS. It does not include military science and physical education courses (Office of the Dean, 2010). A cumulative APS (APSC) of 2.00 or higher is required for graduation.

b. Military Program Score (MPS)

The MPS is the composite score reflected in the accumulated cadet performance in required military development and core military science courses. The eleven required MD courses are 76 percent of the MPS, while the eight core MS courses comprise the remaining 24 percent. Annex A of the Greenbook lists summer training, military duty performance during each term and military science courses during the academic year as elements of the MPS. The following formula conveys how the MPS is calculated: MPS = .70(MD) + .30(MS) (Planning, 2010)

c. Military Development (MD)

The MD grade is a subjective evaluation of cadet leader performance, during the four-year West Point experience (USCC, 2012).

d. Military Science (MS)

MS consists of three military science core courses designed to enhance the professional military education of cadets and develop the foundational military skills and troop-leading procedures required of junior officers. Warfighters' lecture series, joint professional military education, tactical decision-making exercises, combat simulations and faculty experience complement and reinforce military science (core) courses. Selected basic officer leadership course (BOLC-A) tasks are also trained and evaluated in MS courses (Planning, 2010).

USMA publications confirmed MPS weights are progressive activities completed at higher levels of responsibility generally have greater weight. A cadet must achieve a cumulative MPS (MPSC) of 2.00 or higher by the end of third-class (junior) year and maintain it through the conclusion of first-class year.

e. Physical Performance Score (PPS)

The PPS is an annually reported score documenting a cadet's performance during instructional coursework, physical fitness testing and competitive sport participation (Office of the Commandant of Cadets [Whitebook], 2011).

f. Instructional coursework (IC):

IC is composed of two areas. The first area is comprised of the basic activities relevant to military duties (e.g., combatives, boxing, military movement, survival swimming, personal fitness and development). The second area promotes physical development in a wide variety of activities (e.g., rock climbing, tennis, alpine skiing, cycling and SCUBA) (Whitebook, 2011).

g. Fitness Testing (FT):

FT includes three areas. First, each cadet must develop and implement a personal fitness program while at the Academy. Second, cadets must participate in and pass the Army physical fitness test each semester. Lastly, cadets must pass the indoor obstacle course test during their junior year (Whitebook, 2011).

h. Competitive Sports:

Competitive sports participation is vital to a cadet's development and is a "precursor to success" (Whitebook, 2011). General Alexander Haig noticed, "Sports provided the only peacetime activity where the stressors simulated those on a battlefield." General Omar Bradley valued the resultant group cooperation. General Douglas MacArthur, as USMA Superintendent following World War I, required every cadet to participate in organized athletics because he believed athletes made the best Soldiers (Whitebook, 2011). In fact, every cadet is required to memorize General MacArthur's famous quote, "Upon the fields of friendly strife are sown the seeds that upon other fields, on other days, will bear the fruits of victory."

To evaluate performance, USMA used a subjective rating called the character in sports index (CSI). CSI measures the following characteristics: sportsmanship; mental toughness, perseverance, winning spirit; unselfishness; coachability, attitude, teachable spirit; playing ability; and time (Whitebook, 2011). A cumulative physical program score (PPSC) of 2.0 is required to graduate. The following formula illustrates how the PPS is calculated:

PPS = .50 (IC) + .30 (FT) + .20 (CSI).

8. Retention

In 1987, then USMA superintendent, Lieutenant General (LTG) Dave Palmer revised the mission statement and, for the first time, developed a purpose statement. The mission statement added "…inspire each (graduate) to a lifetime of service to the nation"; the purpose became "provide the nation with leaders of character who serve the common defense" (Stanton, 1995). The revised statements clarified "what" and "why" for West Point. Interested personnel (e.g., congress, cadet candidates) then understood the short-term (uniformed service in the regular Army) and long-term (service to the nation) responsibilities for graduates (Stanton, 1995).

In *Preparing for West Point's Third Century, A Summary of the Years of Affirmation and Change,* 1986-1991, Larry R. Donnithorne writes, "West Point graduates will advance in the Army as far as their talents and the needs of the service take them. Their dedication to selfless service, even beyond the time in uniform is both a national need and a historical expectation. They are to be leaders for a lifetime" (Stanton, 1995). LTG Palmer's decision later helped build USMA's relevance in the wake of Army downsizing and eventually attracted those committed to serving national needs, during and after uniformed service.

Officers are required to serve an active duty service obligation (ADSO) upon receiving their commission. The service obligation is five years for USMA graduates (six years for aviators), four years for reserve officer training corps (ROTC) scholarship recipients, and three years for others (non-scholarship ROTC graduates, officer candidate school graduates, and direct appointees) (Department of the Army Headquarters, 2007). At the end of the service contract, officers have the option to terminate their service or remain on active duty.

Circumstances influencing a decision to stay or leave the Army ranks are different for each officer. Between 1950 and 1981, the continuation rate of USMA graduates who chose to stay in the Army beyond six years decreased from 77 percent to 70 percent. A downward trend persisted until the class of 1989, when the continuation rate rose from around 45 percent to 48 percent (Stanton, 1995). Although, LTG Palmer's mission statement became relevant for

a period, tolerating the departure of graduates immediately after their ADSO for (government) civilian work, it failed to communicate the nation's true hope for West Pointers.

The current USMA mission statement specifies a "…career of professional excellence and service to the Nation as an officer in the United States Army." The contrast between the two mission statements is that the old mission statement associates career with both uniformed and civilian service, whereas the current mission statement specifies career in the capacity of a U.S. Army officer. This distinction might underscore why USMA officers, over time, stay in the Army beyond their commitment and why many depart at their first opportunity. As military officers, graduates under the current mission statement, possess a sense of commitment and readiness to serve their country fully knowing USMA expects them to serve as a U.S. Army officer. On the other hand, officers under the previous, and more general, *service to nation* mission statement might consider the possibility of civilian service at some point.

Retention is an important issue for any organization that wants to maintain an educated, highly specialized and all-volunteer force. For the U.S. Army, factors that affect the turnover of Army officers are subjective and difficult to measure accurately. Yet, the reasons an officer stays or leaves seem comparable to those in the civilian population. In an NPS thesis, Genc (2008) hoped to identify reasons for separation of USMA graduates by investigating deployment length and deployment frequency during the global war on terrorism (GWOT), year groups 1994 through 2001.

Genc's research revealed the main factors that affected retention were economics (better job options, higher earnings), better (or stable) living locations, satisfaction with military life, harmony of dependents with military lifestyle, and psychological reasons (Genc, 2008). Interestingly, Genc found officers who deployed to non-hostile environments for a period of more than fifteen months were 23 percent more likely to leave (the Army) than their pre-GWOT peers (Genc, 2008). This signal is counterintuitive. Genc observed non-hostile deployments negatively affect retention and cited the following:

> Existing research suggests '(hostile) deployments increase the job satisfaction and resulted with a higher retention…results supported previous studies that found deployment had a positive effect on job satisfaction and increased the level of personal fulfillment, thus, lead to the decision to stay more on the military'. (Genc, 2008)

Britt, Adler, & Bartone (2001) wrote about the relationship between job satisfaction and hardiness. They found hardiness "associated with being engaged in meaningful work during the deployment, which was strongly associated with deriving benefits from the deployment months after it was over." Similarly, Duckworth et al. (2007) examined another personality factor called grit as an indicator of retention for two USMA classes–2004 and 2006. The studies showed grit as a predictor of retention "above and beyond" WCS and FFM Consciousness (Duckworth et al., 2007). Commenting on the Duckworth et al. (2007) study, Maddi et al., (2012) noted, "Cadets who were retained were twice as likely to have higher grit scores as compared with cadets who were separated…." Nonetheless, in training or deployed environments, officers high in grit may have personal or familial challenges to overcome before deciding to make the military a career.

A naval postgraduate school (NPS) thesis by Gjurich (1999), expressed similar thoughts. Gjurich cited a 1989 document that attributed officers' reasons to leave military service to "dissatisfaction with the military lifestyle, civilian career opportunities and security, and family status" (Gjurich, 1999). Additionally, Gjurich's analysis uncovered variables that increased retention, namely, commissions from ROTC programs and various levels of postgraduate education

(Gjurich, 1999). We infer from his results that Academy (e.g., Naval Academy or USMA) graduates tend to leave the service at a higher rate than ROTC officers do.

Gjurich's thesis generated a viable timeline for a military officer's career and hypothesized an officer's first five years as a period of mutual study and discovery between him and his organization. Between the fifth and tenth year, the officer discovers where he belongs in the organization before he subsequently decides to remain or depart his chosen profession.

The aforementioned research admits the difficulty of any model to predict retention for a specific individual (Gjurich, 1999) and it is difficult to verify, in a timely manner, which circumstances motivated an officer's departure (Genc, 2008). Moreover, USMA's mission statement, perhaps purposely, fails to define the duration of a "…career of professional excellence and service to the Nation as an officer in the United States Army." Perhaps there is a personality factor positively related to retention that we could explore. Could hardiness be that factor?

D. SUMMARY OF LITERATURE REVIEW

Table 1 contains a summary of the research documented in the literature review. Prior research findings reveal (1) CEER, hardiness, and WCS predict leader performance (MD grades, MPS); (2) mental ability (SAT Score) inversely predicts MPS. Second, hardiness and WCS predict CPS. Thirdly, grit and hardiness predict retention. Variables which previous research recognized as successful predictors belong to the following categories:

- Leadership Performance
    - Outcome: MD grades, MPS
    - Predictors (+): CEER, hardiness, WCS
- Cadet Cumulative Performance
    - Outcome: CPS
    - Predictors (+): hardiness, WCS

- Retention
    - Outcome: Years retained
    - Predictors (+): Grit, hardiness

Author	Study Outcome(s)	Study Predictor(s)	Results	Predictor Correlates
Clark (2007)	Academic Success (GPA)	Big Five	Academic Success Pos. rel. to Conscienciousness	Morningness pos. rel. to Conscienc.
		Sleep (Morningness-Eveningness)	Not rel. to Academic Success	
		Sleep Quality (Actigraphy Watches)	Not rel. to Academic Success	
Bartone (2002)	Leader Performance (Upperclass MD grades)	Spatial Judgment battery	No Cognitive or Personality Predictors rel. to Leader Performance	
		Logical reasoning battery		
		battery		
		Problem solving battery		
		Big Five (NEO- Analog)		
		CEER	Leader Performance Pos. rel. to CEER	
Bartone (2009)	Leader Performance (Summer, Academic YR, Combined Upperclass MD grades)	Psychological Hardiness	Summer Leader Performance Pos. rel. to hardiness	No correlation with Gender, CEER
			Academic Leader Performance Pos. rel. to hardiness	
		Big Five	Summer Leader Performance Pos. rel. to Extraversion	
			Academic Leader Performance Pos. rel. to Conscientiousnes	
		Social Judgement	Summer & Academic Performance slightly rel. to Soc. Judgment	
		Gender	Not rel. to Summer Leadership Performance	Conscienc., Agreeableness
		CEER	Not rel. to Summer Leadership Performance	Negatively rel. to Neuroticism,
			Academic Leader Performance Pos. rel. to CEER	
Maddi (2012)	Cadet Performance Score & 1st-Year Retention (Freshmen)	WCS	Retention Minimally -Pos. rel. to WCS	Correl. with Hardiness
			CPS Pos. rel. to WCS	
		Hardiness	Retention Moderately-Pos. rel. to Hardiness	
			CPS Extremely-Pos. rel. to Hardiness	
		Gritt	Retention Extremely-Pos. rel. to Grit	WCS
			CPS Pos. rel. to Grit	Correl. with Hardiness
Bartone (2013)	Military Performance Score (Senior YR) & Adaptability (Self-rate, Supervisor-rate 3 YR post-USMA)	Psychological Hardiness	MPS Pos. rel. to Hardiness-Control	
			MPS Pos. rel. to Hardiness-Commitment	
			MPS Negatively rel. to Hardiness- Challenge	
			Adaptability (Self) Pos. rel. to Hardiness-Control,	
			Adaptability (Supervisor) Pos. rel. to Hardiness-Control	
			Adaptability (Supervisor) not rel. to Hardiness-Commitment, Challenge	
		SAT Score	MPS Negatively rel. to SAT	
		WCS	MPS Pos. rel. to WCS	

Table 1. Literature Review Summary

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METHODS USED

A. DATA DESCRIPTION

The current study used historic data obtained from OIR for cadet year groups 2005, 2006 and 2007. At the researcher's request, and in concert with previous literature, OIR originally released 42 variables. OIR did not release data pertaining to the FFM, sleep quality, Morningness-Eveningness, or cognition (spatial judgment, logical reasoning, social judgment, and problem solving).

The researcher separated the data into three groups. The first group consists of pre-admission variables, used to develop a hardiness predictor; the second group includes post-admission predictors (including hardiness) for retention. All (remaining) variables identified as non-predictors comprise the third group.

We discarded 10 of the original variables, bringing the useable variable count to 32. In particular, we explain two identifier-variables, personal identification number (PIN) and "class admitted to." Each observation had a PIN for the protection of human subjects. "Class admitted to" simply communicated which cohort each PIN belonged. These two variables helped align data, ensuring consistency, throughout the data compilation process. We eventually discarded the other eight variables because of either redundancy or lack of necessity. However, a few of the eight variables served a special purpose.

Specifically, "graduation date from USMA" and "years of service," verified information gained from other variables. "Graduation date" and "class admitted to" helped identify which cadets graduated on time, (with original cohort). We excluded cadets who did not graduate on time from the analysis. The reason for this was to guarantee consistency throughout the data set. Similarly, "years of service" and "active duty status" validated which graduates were retained, and if so, how many years of active service they amassed. The researcher decided that the dichotomous criterion variable "active duty status" sufficiently communicated retention, as well as, if not better than, the numeric variable "years of service." See Appendix C for a by-variable breakdown of variable type and number of levels (or range, where applicable).

B. DEMOGRAPHICS OF THE ARCHIVE

There were 3,716 records in the data set, of which 587 were females and 3,129 were males. Table 2 shows self-reported demographics, including race, gender, and graduation status.

YG	Admits	Gender		RACE							Seperated	Graduated
		F	M	A	AI	B	C	H	O	U		
2005	1198	193	1005	93	10	100	899	70	18	8	257	941
2006	1193	200	993	79	10	72	930	80	16	6	310	883
2007	1325	194	1131	95	11	64	1038	100	10	7	300	1025
TOT	**3716**	**587**	**3129**	**267**	**31**	**236**	**2867**	**250**	**44**	**21**	**867**	**2849**

A- Asian, AI- American Indian, B- Black, C- Caucasian, H- Hispanic, O- Other, U- Unknown

Table 2. Demographics of the OIR Original Data

C. MISSING VALUES

Using descriptive statistics, we inspected the records for uniformity and consistency and accounted for problematic entries (e.g., missing data, outliers). The USMA experience spans 47 continuous months; yet, a number of cadets end their career prematurely (e.g., separation from the academy) or delayed (e.g., graduating in a different cohort due to academic failures, medical reasons, etc.). For the hardiness data set, all observations (cadets) began and ended their USMA career together. This ensured that every cadet in the data set had the same opportunities to affect their final academic, military, physical performance score as their peers. An example showing why this is important follows:

- A cadet enters USMA with YG 2005 as a Plebe. Because of academic trouble, USMA holds the cadet back one year, forcing him to join YG 2006. The cadet, also an intercollegiate athlete, receives an injury a year later. The injury results in training absences due to post-surgery recovery. However, the cadet possesses potential for leadership and, based on the recommendations of his cadet and Army officer Chain of Command, USMA retains him. However, the cadet never catches up to YG 2006 peers in terms of credit hours. Thus, he graduates (and commissions) late, in December, rather than May.

Categorical variables with entries coded as “unknown” or “other” created additional problems with the analysis. If an “unknown” or “other” categorical level proved significant at the completion of analysis, we faced the challenge of explaining it. Fortunately, the problematic cases were few, remedied by deletion from the data set.

Table 3 identifies, for the hardiness data set, the number of cadets who had missing scores. Similarly, Tables 4 and 5 document problematic entries for the two retention data sets (graduation versus separation; active duty versus loss). Reasons for the missing values remain unknown.

Hardiness Data Set	
Original data set entries: YG 2005, 2006, 2007	**3716**
Entries missing hardiness scores	-138
Entries with "unknown" political views	-155
Entries with "unknown" race	-17
Entries with type of high school "other"	-25
Final data set entries	**3381**

Table 3. Problematic Entries: Hardiness Data Set

Graduation versus Separation Data Set	
Original data set entries: YG 2005, 2006, 2007	**3716**
Graduates failing to graduate on time	-149
Entries missing hardiness scores	-138
Entries missing cadet performance data	-279
APS, MPS, PPS, or CPS	
Final data set entries	**3150**

Table 4. Problematic Entries: Graduation versus Separation Data Set

Retention Data Set #2	
Original data set entries: YG 2005, 2006, 2007	**3716**
Separated cadets	-864
Graduates failing to graduate on time	-139
Entries missing hardiness scores	-99
YG 2005, 2006 graduates branched aviation	-319
YG 2005, 2006 graduates branched med. corps	-17
YG 2005, 2006 graduates branched "other"	-21
YG 2007 (< 6 years in service)	-834
Final data set entries	**1423**

Table 5. Problematic Entries: Active Duty versus Loss Data Set

D. ANALYSIS PROCEDURE

1. Hardiness and Simple Linear Regression

In the hardiness data set, we have a mixture of categorical, continuous numeric and integer variables (see Appendix C). Furthermore, our response is continuous, leading us to use linear regression. Linear regression is a useful way to conduct regression analysis, accounting for both categorical and numeric inputs.

First, we identified variables susceptible to multicollinearity using correlation tables and/or variance inflation factor (VIF) diagnostics. Second, we used stepwise regression techniques to develop a hardiness predictor. Stepwise regression systematically adds or drops predictors at each step depending on which reduces the akaike's information criteria (AIC) the most. AIC measures model quality, although it does not guarantee the goodness of fit. The "forward" process of stepwise finds an appropriate model between the null ("main effects") model and the full model while the "backwards" process works in the opposite manner. Both routes identify the same significant variables. We developed various models (main effects and variable-interaction[5]) recommended by the stepwise method. We used the statistical computing software "R," which contains a stepwise function with options for the forward and backward methods.

Third, we analyzed the difference in mean response for each predictor level using the Kruskal Wallis test statistic, analysis of variance (ANOVA) and Tukey comparison test. Lastly, for models containing significant interaction terms ("p-value," $p < .05$), we created interaction plots. Interaction plots, typically produced for two interacting categorical variables and a response variable, showed us how the average hardiness of one variable varied as the other variable changed.

Additional explanations and mathematical formulae are located in Appendix E.

2. Retention and Logistic Regression

We used generalized linear models (GLM) to predict retention. Retention, a binary outcome with binomially distributed errors, requires a function to assign a number value to the two response values "YES" and "NO." If we restrict the domain to (0, 1), we find a useful way to obtain probabilities for predicting our response. We associate a probability close to zero with the response "NO" and probabilities near one with "YES." See Appendix F for additional details and mathematical formulation.

After fitting several of the GLMs (including stepwise and clog-log link), we inspected the significance levels (p-values) of the variables. We then

[5] For example, main effects: *Hardiness = gender + race + parents' degree*; variable-interaction: *Hardiness = (gender)(parents' degree)+(race)(parents' service)+log(APSC)+…*

constructed a generalized additive model (GAM) with smoothing functions applied to the numeric predictors before visualizing the partial residual plots to determine which transformation(s) to make, if any. After making the necessary transformations, we fit additional GLMs and compared their performance by using ANOVA. Next, we developed a confusion matrix to see how accurately our model classified the response probabilities.

Lastly, we performed cross validation (CV) to assess over-fitting, "a situation when the model requires more information than the data can provide" (Starkweather, 2013). CV randomly divides the data into a specified number (e.g., k=10) of groups. In CV, we use k-1 groups as a subset of the data and call it the "training set." We term the remaining group, the "test set." CV generates a GLM from the training set then uses the test set to assess its prediction accuracy. An "R" software function, called "cv.glm," iterates CV k-1 times, using a different test set each time, to compute the cross-validation estimate.

RESEARCH RESULTS

A. HARDINESS MODEL 1

1. Multicollinearity

We explored the relationship between hardiness and the remaining 18 pre-admission variables using the statistical package "R." We inspected the variables for sources of multicollinearity. Table 6 contains the correlations between hardiness (hrdns2) and pre-admission variables.

	gend	race	f.deg	m.deg	poliv	pGrad	pServ	typ.hs	wcs	ceer	pae	cls	eas	aas	fas	hrdns2
gend	1.00															
race	0.06	1.00														
f.deg	-0.01	-0.01	1.00													
m.deg	0.00	0.04	0.13	1.00												
poliv	-0.10	-0.10	0.03	-0.06	1.00											
pGrad	0.04	-0.04	0.09	-0.04	0.07	1.00										
pServ	0.03	0.03	0.07	0.00	0.05	0.29	1.00									
typ.hs	-0.04	0.00	0.02	-0.03	0.06	0.00	-0.03	1.00								
wcs	-0.01	0.06	-0.06	-0.04	-0.09	0.01	0.06	0.06	1.00							
ceer	-0.01	0.07	-0.06	-0.03	-0.09	0.00	0.05	0.07	**0.89**	1.00						
pae	0.01	-0.10	-0.01	-0.01	0.02	0.05	0.05	0.00	0.13	-0.13	1.00					
cls	-0.02	0.03	0.00	-0.03	-0.01	0.01	0.02	0.02	0.35	-0.06	0.16	1.00				
eas	0.03	0.00	0.00	-0.02	-0.05	-0.01	-0.02	0.03	0.36	0.12	-0.06	**0.66**	1.00			
aas	-0.04	0.03	0.00	-0.03	0.03	0.02	0.05	-0.01	0.04	-0.27	0.27	**0.66**	-0.09	1.00		
fas	-0.10	0.05	-0.01	0.03	-0.03	-0.01	0.01	0.04	0.35	0.29	0.03	0.24	0.10	0.00	1.00	
hrdns2	-0.09	0.02	-0.01	-0.01	0.04	0.02	0.01	-0.01	-0.04	-0.08	0.06	0.06	0.07	0.02	0.02	1.00

Table 6. Hardiness Correlation

We saw no significant correlation between hardiness and any of the numeric variables. However, we noticed strong correlation between several of the pre-admission variables (WCS versus CEER, r = 0.89; EAS versus CLS, r = 0.66, AAS versus CLS, r = 0.67). The correlations made sense because WCS and CLS relate in the following way:

WCS= (6 x CEER) + (3 x CLS) + (PAE SCORE)

CLS= (EAS+ AAS+ FAS) / 3

Strong correlations resulted in the removal of WCS and CLS from the data set. Additionally, we discovered a strong correlation between the categorical variables recruited athlete and played sport (playedsport1) (r = 0.86). We removed recruited athlete because, when given the choice, actual participation in intercollegiate athletics interested the researchers more than recruitment. Moreover, retaining "playedsport1" accounts for cadets who "walk-on" to intercollegiate athletic teams.

We completed variance inflation factor (VIF) diagnostics, shown in Table 7, to identify remaining multicollinearity. All VIF values fall below ten, suggesting a lack of significant multicollinearity.

Variable	GVIF	Df	GVIF^(1/(2*Df))
gender	1.07	1	1.03
race	1.32	6	1.02
usmaps	1.33	1	1.15
playedsport1	1.47	1	1.21
ceer	1.59	1	1.26
pae	1.16	1	1.08
eas	1.11	1	1.05
aas	1.39	1	1.18
fas	1.13	1	1.06
f.degree	1.11	2	1.03
m.degree	1.09	2	1.02
poliview	1.18	5	1.02
pGrad	1.17	3	1.03
pServ	1.20	3	1.03

Table 7. Variance Inflation Factor, Main Effects Model

2. Main Effects Linear Model and Stepwise Regression

We created a linear model with the remaining variables. The proportion of variation in the response explained by these variables was extremely low (R^2= 0.04). Nevertheless, we identified the most significant variables, listed in Table 8, and proceeded to develop a hierarchical (stepwise) regression model.

The stepwise regression model found the same significant variables as those shown in Table 8. However, we did not see an improvement in the coefficient of multiple determination (R^2=.03). Notice also, that several of the variables have coefficient estimates at or near zero indicating their weakness in predicting hardiness.

Variables	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.826	0.153	11.943	<.001
genderMale	-0.079	0.014	-5.471	<.001
playedsport1	-0.029	0.014	-2.141	0.032
ceer	-0.001	0	-5.422	<.001
pae	0	0	3.879	<.001
eas	0	0	4.087	<.001
m.degreeGradSchool	0.040	0.018	2.177	0.030

Table 8. Significant Hardiness Predictors, Stepwise Regression

Appendix G contains a pairs-plot of the significant predictors (Table 8) and hardiness. Consistent with the regression results, the plot reveals no apparent relationships.

3. Kruskal-Wallis and Tukey Mean Comparison Test

Residual plots, also located in Appendix G, did not show any violation of assumptions. We used the Kruskal-Wallis test to compare the difference in average hardiness across the significant (categorical predictor) levels to confirm this (see Table 9). The only predictor whose average hardiness differed between levels turned out to be gender. Inspection of the hardiness values revealed that a higher percentage of males achieved low (≤1.5) hardiness scores while a higher percentage of females achieved high (> 1.5) hardiness scores. A strip chart visualizes this occurrence, shown in Figure 2.

Variable	chi-squared	df	, p-value
gender	28.001	1	<.001
playedsport1	0.038	1	0.847
typehs	3.876	4	0.423
f.degree	1.879	2	0.391
m.degree	5.505	2	0.064

Table 9. Kruskal-Wallis Test: Hardiness versus Categorical Predictors

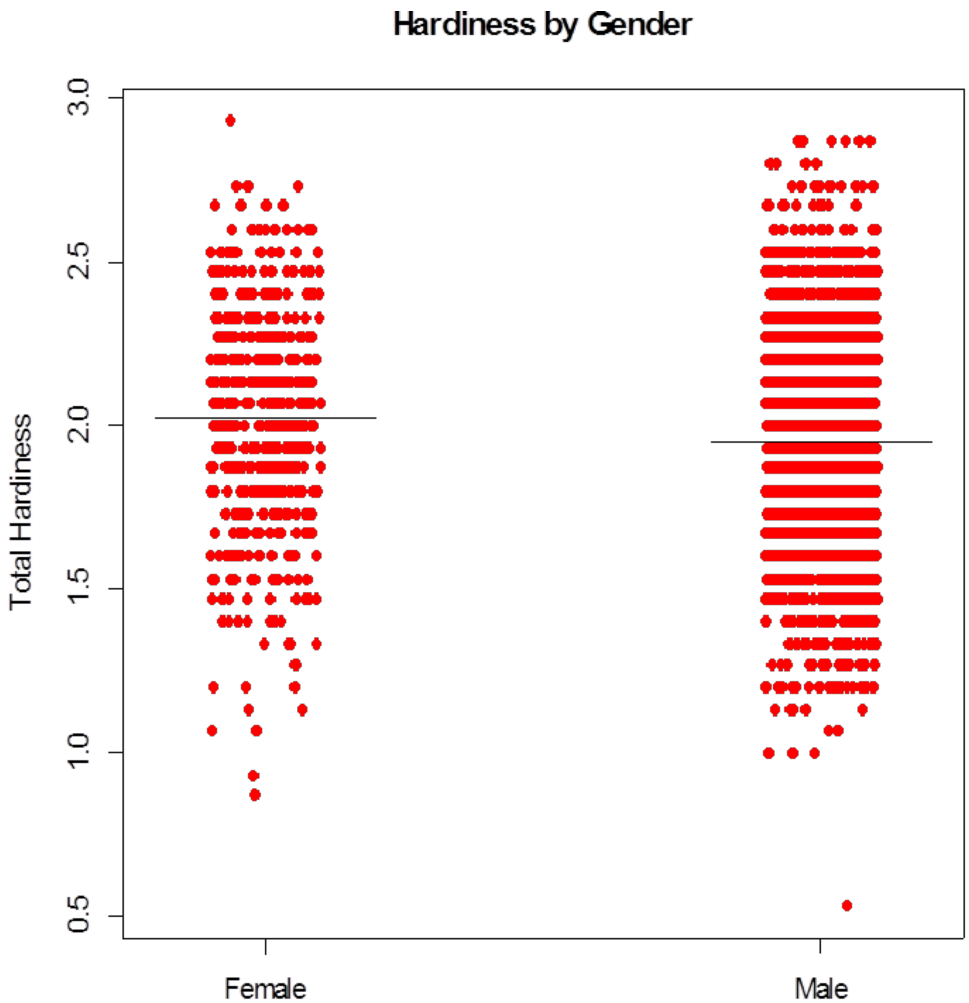

Figure 2. Hardiness versus Gender

The Tukey test for determining differences between means confirmed that the average hardiness between males and females differed. However, while significant, the effect size was negligible ($p < .001$). Table 10 shows the difference (in means) and confidence interval information.

95% family-wise confidence level			
Lower	Upper	Difference	p-vale adjusted
-0.101	-0.044	-0.072	<.001

Table 10. Tukey Comparison of Average Hardiness by Gender

4. Stepwise Regression Linear Model with Interaction

We conducted similar procedures for a stepwise linear model with interaction between the terms. Interestingly, several 'new' predictors showed as significant, in addition to those with interaction. See Table 11 for the significant predictors from this model. In addition, we see our first improvement[6] to the coefficient of determination (R^2=0.053) and to the beta "estimates" in Table 11.

Variables	Estimate	Std. Error	t value	Pr(>|t|)
genderMale	-0.261	0.087	-3.006	0.003
ceer	-0.002	0.001	-2.948	0.003
fas	0.012	0.005	2.479	0.013
pae	-0.002	0.001	-2.420	0.016
typehsPublic	6.994	3.453	2.025	0.043
typehsPriv.Rel	7.247	3.474	2.086	0.037
fas:typehsPublic	-0.010	0.005	-2.056	0.040
f.degreeHighSchool	-0.141	0.030	-4.706	<.001
genderMale:f.degreeHighSchool	0.149	0.033	4.560	<.001
pae:aas	0	0	3.016	0.003
fas:typehsPriv.Rel	-0.010	0.005	-2.126	0.034

Table 11. Significant Hardiness Predictors, Stepwise with Interaction

[6] We see beta coefficients > 1 as an improvement over beta coefficients < 1.

Type of high school (public and private religious) appears positively related to hardiness and is the first variables with coefficient estimates greater than one. However, the relationship between public school and hardiness is suspicious since the population is predominantly educated in the public school system (only 658 out of 3,381 data points correspond to private high school students).

Interaction between faculty appraisal score (FAS) and public high school or private religious high school barely, yet inversely, relate to hardiness.

Next, for both genders, less-educated fathers appear to decrease hardiness while less-educated fathers of male cadets relate positively to hardiness.

5. Analysis of Variance between Models

We conducted ANOVA on the two stepwise regression models, (Table 8 and Table 11) and discovered that the “full” (more complicated, stepwise with interaction) model performed better than the reduced model (no interaction terms). See Table 12.

Model 1: hrdns2 ~ stepwise					
Model 2: hrdns2 ~ stepwise with interaction					
Model	**Res.Df**	**RSS**	**Df**	**Sum of Sq**	**Pr(>Chi)**
1	3372	306.72			
2	3342	298.59	30	8.1259	<.001

Table 12. Hardiness Stepwise Model ANOVA Results

In summary, we achieved coefficient estimates less than one, except for private religious and public high school types, in the stepwise interaction model. Nearly all predictors contributed poorly to total hardiness. However, the stepwise model with interaction performed better, signifying the apparent relationship of several predictors to hardiness, when combined (interaction).

B. HARDINESS MODEL 2

We created a second hardiness model to determine the predictive power of hardiness within a target group of the data. On the premise that athletes undergo trials similar to those experienced in the military lifestyle, we chose the USMA varsity football team. Table 13 shows a summary of the data (*N*= 146).

USMAPS		AVERAGE HARDINESS (H)				FATHER'S DEGREE LEVEL		
Yes	No	Total H	H-Com.	H-Con.	H-Cha.	High Sch.	College	Graduate
36	110	1.97	2.08	2.07	1.76	53	65	28

RACE						MOTHER'S DEGREE LEVEL		
Asian	Am.Indian	Afr.Amer	Cauc.	Hisp.	Unk.	High Sch.	College	Graduate
1	1	30	111	2	1	54	73	19

POLITICAL VIEWS					TYPE OF HIGH SCHOOL			
Far Left	Liberal	Moder.	Conserv.	Far Right	Public	Priv-Relig.	Priv-Gen.	Priv-Mil.
0	20	65	61	0	120	21	4	1

PARENTS' MILITARY SERVICE				PARENT USMA GRADUATES			
Both	Father	Mother	Neither	Both	Father	Mother	Neither
12	43	3	88	0	5	0	141

Table 13. Data Summary, USMA Football Player Data Set

1. Multicollinearity

We constructed a correlation table for the full set of variables for the football team data set in order to identify potential sources of multicollinearity (see Table 14).

	race	usmaps	f.deg	m.deg	poliw	pgrad	pserv	typ.hs	wcs	ceer	pae	cls	eas	aas	fas	cm2	co2	ch2	hrdns2
race	1.00																		
usmaps	-0.29	1.00																	
f.deg	-0.08	0.16	1.00																
m.deg	-0.02	0.13	0.20	1.00															
poliw	-0.16	0.06	0.15	0.19	1.00														
pgrad	-0.05	0.02	0.07	0.06	0.22	1.00													
pserv	0.02	0.06	0.24	0.11	0.05	0.23	1.00												
typ.hs	-0.11	0.04	0.07	0.02	0.09	-0.01	-0.01	1.00											
wcs	0.17	-0.38	-0.01	-0.12	-0.17	-0.06	0.05	0.16	1.00										
ceer	0.26	-0.42	-0.04	-0.16	-0.19	-0.04	0.05	0.17	**0.91**	1.00									
pae	-0.26	0.08	-0.02	-0.05	-0.03	0.08	0.09	0.09	0.10	-0.09	1.00								
cls	0.01	-0.07	0.06	0.08	-0.01	-0.12	-0.06	0.06	0.43	0.08	-0.01	1.00							
eas	-0.06	0.01	0.07	0.03	-0.06	-0.11	-0.06	0.10	0.46	0.17	-0.01	**0.87**	1.00						
aas	0.07	-0.07	0.02	0.13	0.12	0.03	0.04	-0.06	-0.07	-0.24	-0.01	0.36	-0.10	1.00					
fas	0.13	-0.25	-0.05	-0.02	-0.04	-0.18	-0.12	-0.02	0.27	0.19	-0.03	0.28	0.15	-0.08	1.00				
cm2	0.20	-0.01	-0.01	-0.03	-0.17	0.00	0.03	0.06	0.04	-0.04	0.13	0.15	0.09	0.13	0.08	1.00			
co2	0.03	0.13	0.09	0.00	0.05	0.11	0.00	0.12	-0.05	-0.12	0.11	0.18	0.18	0.02	0.05	**0.54**	1.00		
ch2	0.01	-0.14	0.01	0.17	0.19	-0.03	0.03	-0.07	-0.03	-0.05	0.10	-0.01	-0.03	0.07	-0.05	0.10	-0.01	1.00	
hrdns2	0.11	-0.03	0.04	0.09	0.06	0.03	0.03	0.03	-0.02	-0.10	0.16	0.14	0.10	0.11	0.03	**0.74**	**0.67**	**0.63**	1.00

Table 14. Hardiness Correlation, Football Team

Again, we see WCS significantly correlated (*r* > |0.5|) with CEER and CLS significantly correlated with EAS. Interestingly, the second hardiness model did not show significant correlation between CLS and AAS for the football players[7], as did hardiness model 1. Lastly, as expected, the hardiness facets correlate with total hardiness. We removed WCS, CLS, and the hardiness facets from the model to minimize the effects of multicolinearity.

2. Main Effects Linear Model and Stepwise Regression

After comparing simple linear and stepwise regression models, we noticed stepwise regression produced a better coefficient of determination (R^2=0.19 and R^2_a=0.11) and four significant terms at the p<.05 level; however, only high school type (public/ private) and mothers degree (graduate) exceeded 0.1. Each of the

significant variables related positively to hardiness. High school type became the

[7] We did not include gender because only males participate in varsity football. Additionally, we saw previously that the difference in hardiness between genders is negligible.

strongest predictor of hardiness in the stepwise method. See Table 15 for the summary of significant variables.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
typehsPriv.Rel	0.492	0.163	3.014	0.003
pae	0.001	0	2.977	0.003
typehsPublic	0.348	0.152	2.295	0.023
m.degreeGradSchool	0.172	0.077	2.239	0.027

Table 15. Significant Football Hardiness Predictors, Stepwise Regression

3. Interaction Model and Stepwise Regression

We created another model with interaction terms and used the stepwise method to identify the significant variables. This model quality appeared to improve greatly (R^2=0.97, R^2_a=0.70). We discovered a great number of significant terms, 36 at the $p<.05$ level; however, only 11 of the coefficient estimates exceeded the value 1.0. Rather than listing every significant interaction term, we list the variable names: mothers' degree level, fathers' degree level, political view, type of high school, race, and USMAPS attendance. Table 16 shows the summary output for the significant terms.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
m.degreeHighSchool	-15.880	3.747	-4.237	0.001
poliviewL	-15.600	6.776	-2.303	0.036
f.degreeGradSchool:typehsPriv.Rel	-6.525	2.381	-2.741	0.015
raceAf.Amer:poliviewL	-1.819	0.684	-2.660	0.018
raceAf.Amer:poliviewM	-1.207	0.437	-2.761	0.015
poliviewL:pServFather	-1.205	0.558	-2.158	0.048
usmapsYes:poliviewM	1.063	0.378	2.814	0.013
usmapsYes:poliviewL	3.094	0.845	3.660	0.002
raceHisp	3.619	1.167	3.100	0.007
raceAf.Amer:pServNeither	6.235	2.167	2.877	0.012
raceAf.Amer:pServFather	7.345	2.280	3.221	0.006
Residual standard error: 0.167 on 15 degrees of freedom				
Multiple R-squared: 0.9687, Adjusted R-squared: 0.6978				
F-statistic: 3.576 on 130 and 15 DF, p-value: 0.00357				

Table 16. Significant Variables, Hardiness Model 2, Stepwise Interaction

Table 16 indicates less-educated mothers, liberal and moderate political views (when present in African Americans players), and educated fathers with cadets/ males who attended private religious school, negatively influence hardiness. On the other hand, moderate and liberal political views, when combined with USMAPS attendance related positively to hardiness. Finally, African Americans with military-fathers, African Americans with non-military parents, and Hispanics relate positively to total hardiness. The model suggests African American football players with military-fathers are more likely to display hardiness.

4. Hardiness, Race and Parents' Military Service

After inspection, race (Hispanics) related less to hardiness than the summary output from Table 16 showed. We believe the small number of Hispanic football players—only two of the 146 observations—inflated their average hardiness.

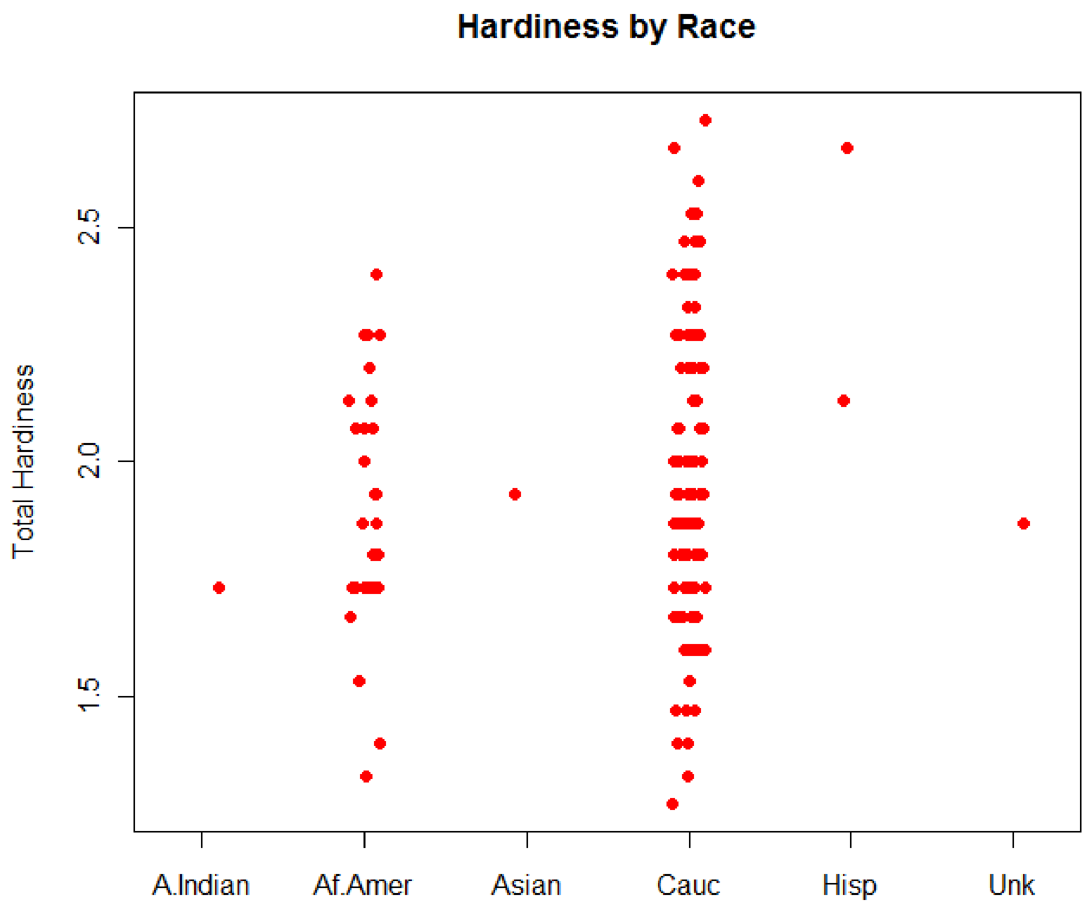

Figure 3. Race versus Hardiness, Football Players

Caucasians and African Americans dominate the population of football players. Caucasians, as the majority, have the highest hardiness average, followed by African American players.

Next, we created an interaction plot to see how the average hardiness score changed between the races as parents' service status changed. See Figure 4. The effect of parents' military service on hardiness is different for African Americans than it is for Caucasians. Caucasian football players' hardiness is highest when both parents serve/ served in the military while African American players' hardiness is highest when only the father served.

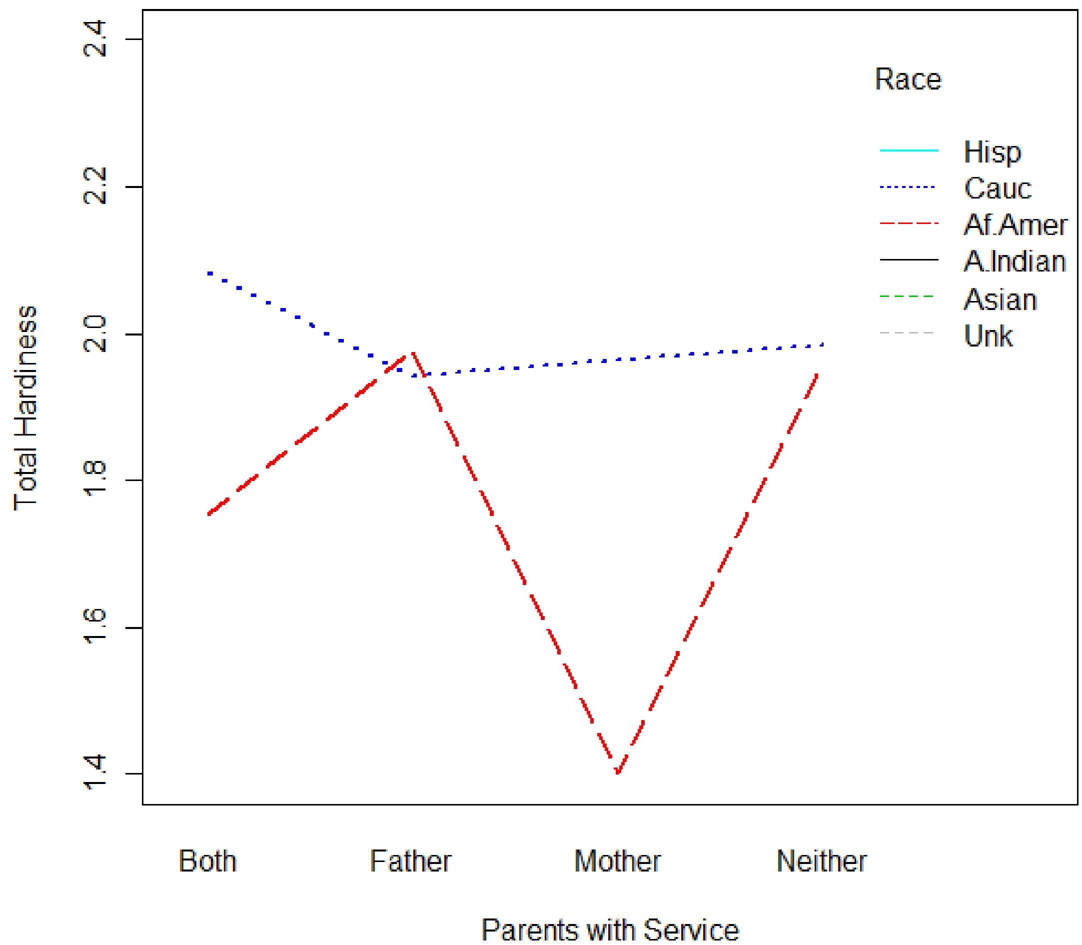

Figure 4. Interaction Plot: Race, Parents' Service and Hardiness

Only one African American player had a military-mother—that player's hardiness score was 1.4. That is the reason for the deep trough in the African American average hardiness over "Mother." If the data contained more African American football players with military-mothers, the interaction plot could change. The other races do not appear in the interaction plot due to lack of representation in the sample (see single dots in Figure 3 over American Indian, Asian, and unknown).

5. Hardiness, USMAPS Attendance and Political View

Next, we investigated USMAPS attendance, political views and hardiness. The average hardiness scores for non-USMAPS and USMAPS players are 1.97 and 1.95, respectively (see Figure 5).

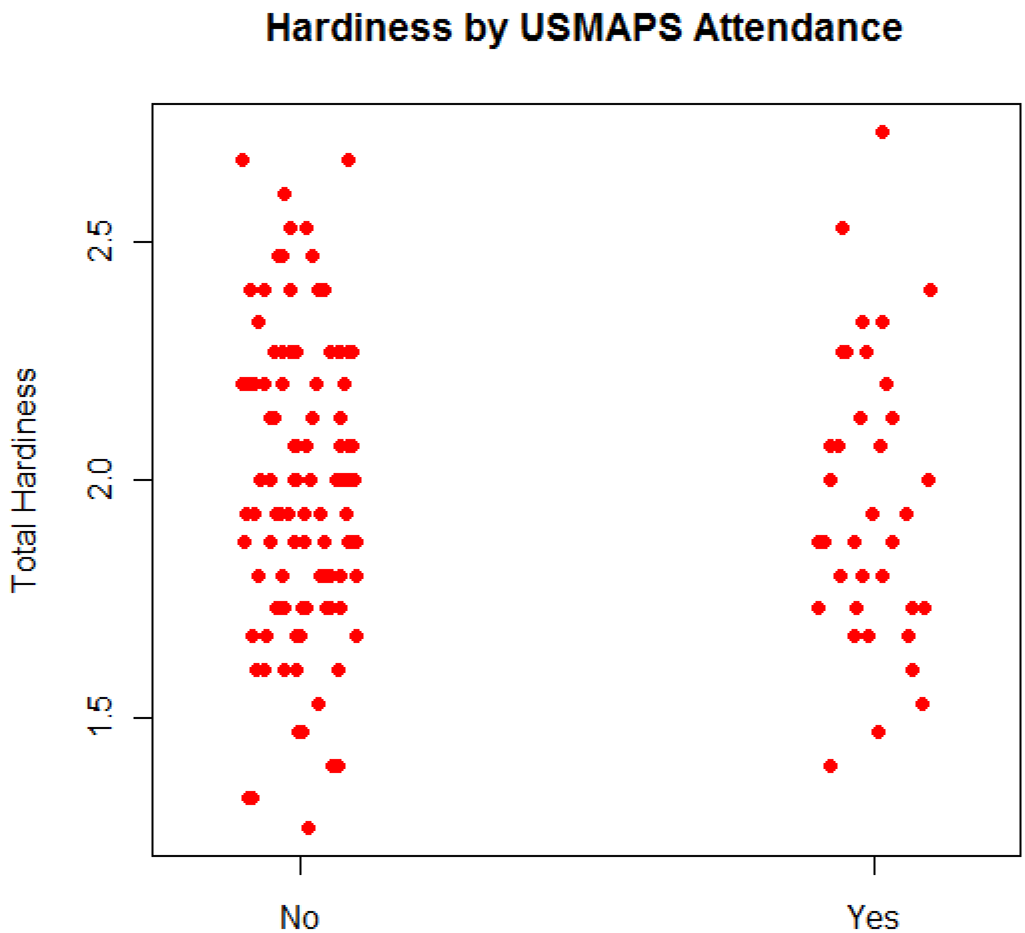

Figure 5. USMAPS versus Hardiness, Football Players

"Far left" or "far right" (political view) occurred in only three of the 146 entries, thereby making the original interaction plot difficult to interpret. Another source of difficulty came from the lack of "far left" USMAPS attendees. Therefore, we imputed "far left" as liberal and "far right" as conservative. The interaction plot shown in Figure 6 indicates the effect of political views on hardiness is generally the same USMAPS players and non-USMAPS players.[8] However, conservative (C) USMAPS players tend to have lower average hardiness.

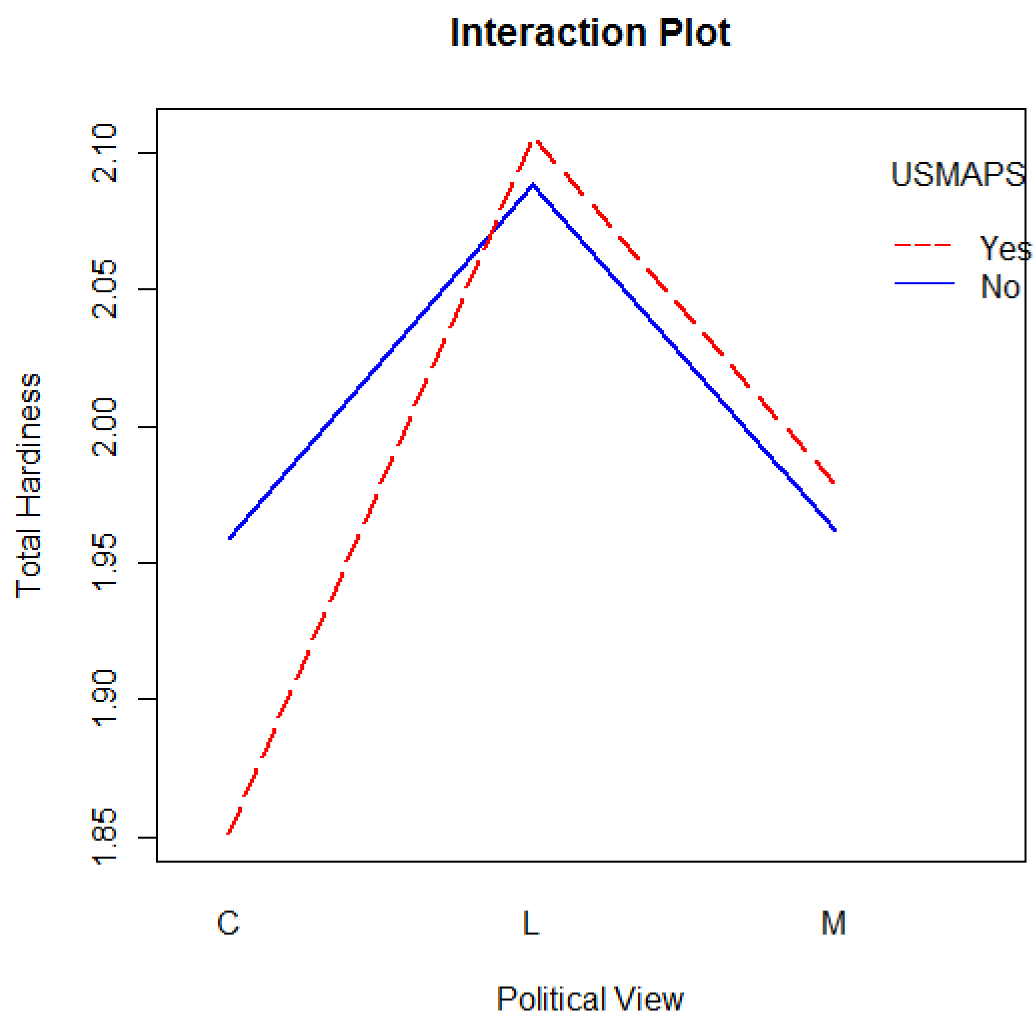

Figure 6. Interaction Plot: USMAPS, Political View and Hardiness

[8] C: conservative, L: liberal, M: moderate political views

6. Hardiness, High School Type and Fathers' Degree Level

Lastly, we investigated the interaction between high school type and fathers' degree level. Figure 7 shows the public and private religious schools dominate the population (average hardiness, 1.97 and 2.03, respectively).

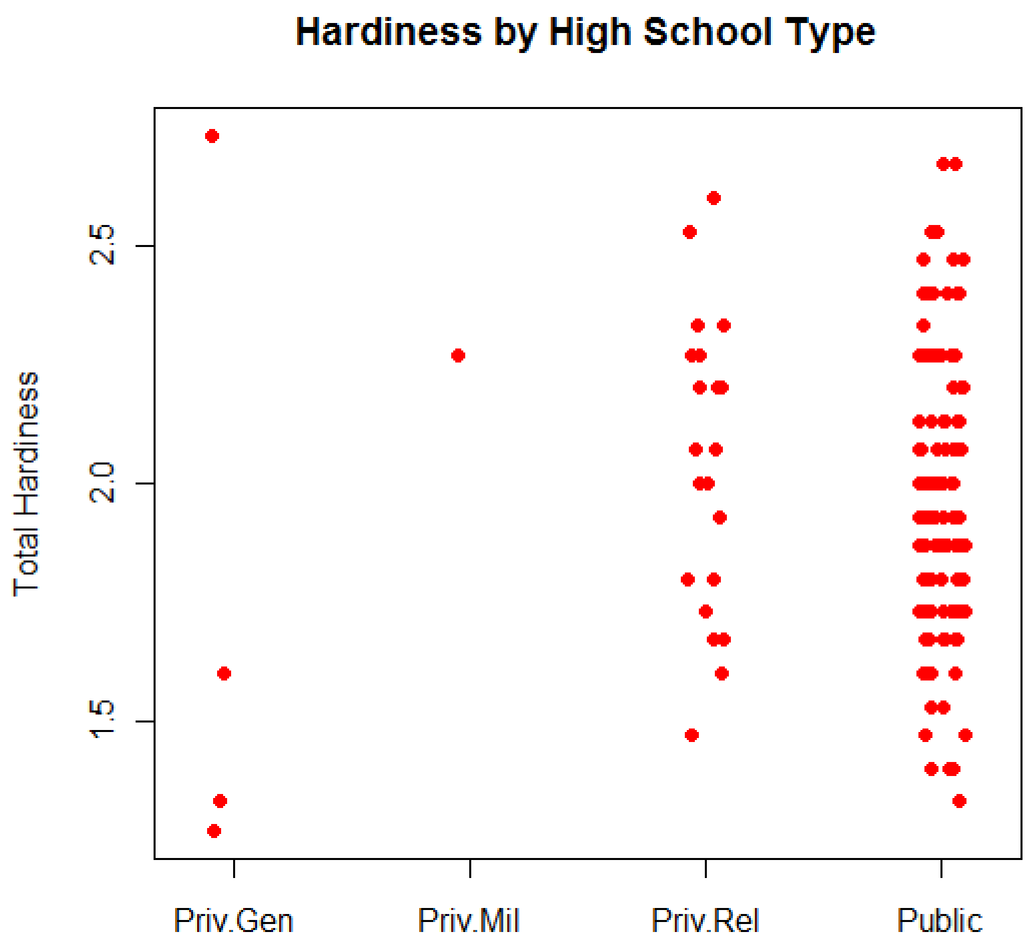

Figure 7. High School Type versus Hardiness, Football Players

We created an interaction plot and noticed average hardiness does not change for public school players as fathers' degree level changes. However, for players educated in private religious high schools, average hardiness decreases as fathers' education level increases. Although, interpretation of private-general schools is limited because of sample size, we notice it favors the behavior of private religious schools.

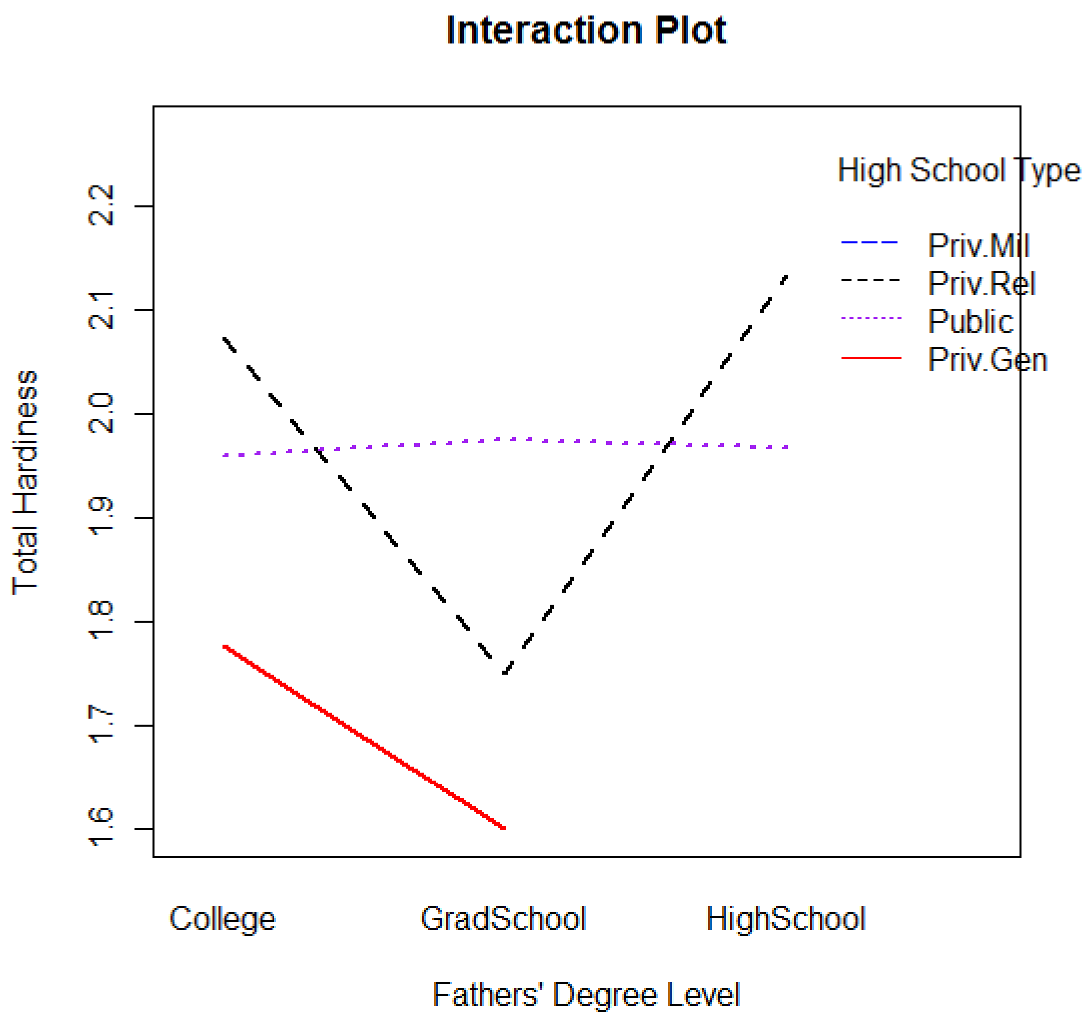

Figure 8. Interaction Plot: High School, Father's Degree and Hardiness

C. RETENTION MODEL 1: GRADUATION VERSUS SEPARATION

1. Multicollinearity

Retention model 1 aims to predict the likelihood of graduation (vice separation) from West Point. First, we inspected the variables for any presence of multicollinearity. Table 17 displays the correlations between the 12 numeric variables (including our response, Graduation Status). We denoted our response variable "Gstat." We did not see any significant correlation between retention and any of the numeric variables. However, we observed significant correlation between two sets of variables (APSC versus CEER, r = 0.61; APSC versus

MPSC, r = 0.54). We were not surprise in the correlations since APSC, CEER, and MPSC are strong academic indicators of performance. The correlation results led to the removal of APSC from the model.

Note: We included a pairs plot of the significant variables in Appendix G.

	cm2	co2	ch2	ceer	pae	eas	aas	fas	apsc	mpsc	ppsc	m.deg	f.deg	typ.a	Gstat
cm2	1.00														
co2	0.49	1.00													
ch2	0.16	0.02	1.00												
ceer	-0.04	-0.17	0.01	1.00											
pae	0.05	0.07	0.02	-0.12	1.00										
eas	0.07	0.06	0.02	0.11	-0.07	1.00									
aas	0.01	0.04	-0.02	-0.26	0.26	-0.09	1.00								
fas	0.07	0.02	-0.05	0.28	0.02	0.10	0.00	1.00							
apsc	-0.01	-0.09	-0.04	**0.61**	-0.03	0.08	-0.14	0.28	1.00						
mpsc	0.08	0.04	-0.05	0.26	0.02	0.17	-0.05	0.26	**0.54**	1.00					
ppsc	0.08	0.03	0.03	0.13	0.30	0.00	0.16	0.16	0.45	0.44	1.00				
m.deg	0.02	0.01	0.00	-0.04	-0.02	-0.01	-0.03	0.03	-0.06	-0.03	-0.04	1.00			
f.deg	0.00	-0.01	-0.01	-0.06	0.00	0.00	0.00	-0.02	-0.06	-0.02	-0.03	0.16	1.00		
typ.a	-0.02	0.03	-0.03	-0.22	0.21	-0.16	0.34	-0.02	-0.13	-0.10	0.10	-0.01	-0.01	1.00	
Gstat	0.03	0.03	-0.05	0.10	0.02	0.04	-0.01	0.09	0.41	0.28	0.31	-0.04	-0.05	-0.05	1.00

Table 17. Retention (Graduation versus Separation) Correlation

2. Logit-link GLM and Stepwise Regression

Next, we created a GLM using the logit-link function and then ran stepwise regression. The stepwise method yielded the same variables as the main effects model but the ANOVA test showed the stepwise with a higher residual deviance. However, the stepwise model yielded a better (lower) AIC value, so we retained it. Tables 18 and 19 show the significant variables from the stepwise (GLM 1) and the ANOVA test, respectively.

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-5.445	0.601	-9.061	<.001
mpsc	1.145	0.138	8.279	<.001
ppsc	1.778	0.149	11.904	<.001
ch2	-0.288	0.099	-2.911	0.004
typ.athVar	-0.358	0.146	-2.456	0.014
f.degreeHighSchool	-0.253	0.114	-2.216	0.027
Null deviance: 2914.5 on 3149 degrees of freedom				
Residual deviance: 2493.5 on 3141 degrees of freedom				
AIC: 2511.5				

Table 18. Significant Retention Predictors, Stepwise GLM 1

Model 1: status ~ typ.ath + m.degree + f.degree + cm2 + co2 + ch2 + ceer + pae + eas + aas + fas + mpsc + ppsc					
Model 2: status ~ typ.ath+f.degree+ch2+pae+mpsc+ppsc					
Model	**Res.Df**	**RSS**	**Df**	**Sum of Sq**	**Pr(>Chi)**
1	3133.00	2490.20			
2	3141.00	2493.50	-8.00	-3.24	0.92

Table 19. GLM 1 Main Effects and Stepwise ANOVA Results

MPSC and PPSC relate positively to retention; hardiness-challenge (ch2), varsity athletes (typ.athVar), and father's degree (high school) relate negatively to retention. PPSC is the strongest indicator of retention among the variables in the model.

Next, we created a second (main effects) GLM (not shown) using the clog-log link to see if it was better than the logit-link model, but it was not. We observed a difference in a deviance of 37.5 between logit and clog-log, in favor of the logit-linked model.

3. Generalized Additive Models

The third model we constructed started with a generalized additive model (GAM), using the original predictors and incorporating a smoothing function on the numeric variables. We plotted the partial residual terms against their predictors to identify variables that needed transformation. The plots in Figure 9 reveal hardiness-challenge, type of athlete, and father's degree appear linearly while MPSC and PPSC appeared logarithmic. Note: the other variables appeared linearly, but we did not include them in the figures to save space.

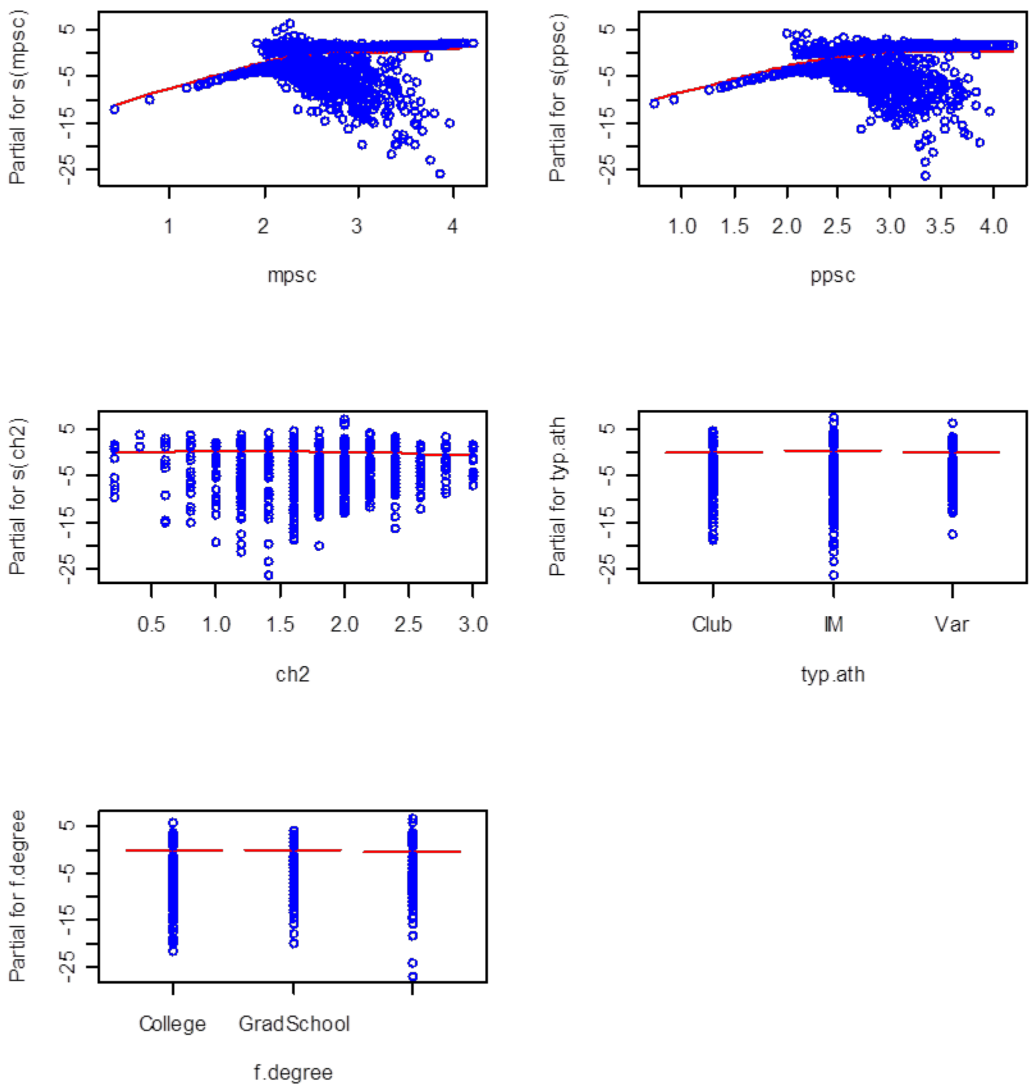

Figure 9. Partial Residuals versus Predictor Plot, GAM

We made logarithmic transformations on MPSC and PPSC, fit a third GLM, and then conducted stepwise regression on the new model. We witnessed an improvement (decrease) in AIC and found an additional significant variable, namely, PAE score. The stepwise from our third GLM (GLM 3) turned out to be our best model. Table 20 contains the summary statistics for the stepwise model with the transformed variables. Equation (1) shows the fitted model.

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-5.739	0.606	-9.471	<.001
log(mpsc)	3.307	0.363	9.102	<.001
log(ppsc)	5.041	0.416	12.114	<.001
ch2	-0.296	0.100	-2.955	0.003
typ.athVar	-0.340	0.147	-2.321	0.020
f.degreeHighSchool	-0.261	0.115	-2.257	0.024
pae	-0.002	0.001	-1.990	0.047
Null deviance: 2914.5 on 3149 degrees of freedom				
Residual deviance: 2459.5 on 3141 degrees of freedom				
AIC: 2477.5				

Table 20. Significant Retention Predictors, Stepwise GLM 3

$$\hat{\eta}_i = \hat{\beta}_0 + \hat{\beta}_1 X_1 + ... + \hat{\beta}_{p-1} X_{p-1} \tag{1}$$
$$\hat{\eta}_i = -5.739 + 3.307 X_{\log(mpsc)} + 5.041 X_{\log(ppsc)} - 0.296 X_{ch2} - 0.340 X_{typ.athVar}$$
$$-0.261 X_{f.\deg ree(high.school)} - 0.002 X_{pae}$$
$$\hat{\pi}_i = \frac{\exp(\hat{\eta}_i)}{1+\exp(\hat{\eta}_i)} = \hat{Y}_i$$

The fitted model ($\hat{Y}_i$) shows hardiness-challenge, varsity athletes, father's degree (high school), and PAE relate inversely to retention (graduation). Next, the model established MPSC and PPSC as positive contributors to retention. The strongest predictors of retention are MPSC and PPSC.

4. Confusion Matrix, Retention Model 1

A confusion matrix helped determine how well stepwise GLM 3 (Table 20) classified the responses. We used the following predicted probability threshold:

$\hat{\pi}_i > 0.77$ retained (graduated), $\hat{\pi}_i \leq 0.77$ separated. This threshold maximized the correct classification rate and minimized the incorrect classification rate. Table 21 shows the confusion matrix.

Raw Numbers		Observed Value	
		Graduate	Separate
Model Predicted	Graduate	2158	443
	Separate	250	299

Percentages		Observed Value	
		Graduate	Separate
Model Predicted	Graduate	83%	17%
	Separate	46%	54%

Table 21. Graduation versus Separation Confusion Matrix

Our model classified 83 percent of those who graduated correctly and classified 17 percent of the graduates incorrectly. Additionally, the model classified 54 percent of those who separated correctly and 46 percent of those who did not separate incorrectly. The model predicted the occurrence of graduation better than it did separation.

5. Cross-validation Results

Using a function from "R," we obtained a CV estimate of 22 percent, which signifies the percent of response variables we misclassified.

D. RETENTION MODEL 2 ACTIVE DUTY VERSUS LOSS

1. Multicollinearity

Similar to the previous models, we assessed the correlation between the variables to detect any significant multicollinearity ($r > |0.5|$). Note the correlations for Retention Model 2 in Table 22.

	typ.ath	m.deg	f.deg	cm2	co2	ch2	ceer	pae	eas	aas	fas	apsc	mpsc	ppsc	babr	A.stat
typ.ath	1.00															
m.deg	0.04	1.00														
f.deg	-0.01	0.13	1.00													
cm2	-0.01	0.02	0.01	1.00												
co2	0.04	0.00	0.00	0.48	1.00											
ch2	-0.02	0.04	-0.01	0.18	0.02	1.00										
ceer	-0.25	-0.04	-0.04	0.01	-0.16	0.03	1.00									
pae	0.24	0.01	0.01	0.07	0.08	0.02	-0.16	1.00								
eas	-0.17	-0.04	0.02	0.08	0.05	0.03	0.10	-0.06	1.00							
aas	0.37	-0.03	0.01	0.00	0.05	-0.02	-0.29	0.29	-0.10	1.00						
fas	-0.01	-0.01	-0.02	0.10	-0.02	-0.02	0.31	0.05	0.09	0.02	1.00					
apsc	-0.14	-0.07	-0.04	0.01	-0.10	-0.02	**0.64**	-0.08	0.08	-0.18	0.31	1.00				
mpsc	-0.09	-0.05	0.00	0.13	0.08	-0.02	0.24	0.01	0.18	-0.05	0.26	**0.52**	1.00			
ppsc	0.12	-0.03	-0.02	0.11	0.04	0.05	0.10	0.32	0.03	0.16	0.23	0.38	0.46	1.00		
babr	-0.03	0.00	-0.08	0.05	0.03	0.07	0.05	0.03	0.04	-0.03	0.02	0.08	0.02	0.06	1.00	
A.stat	-0.08	0.00	-0.01	0.01	-0.03	-0.02	0.06	-0.06	0.06	-0.09	-0.03	0.02	0.06	0.01	-0.02	1.00

Table 22. Retention (active duty versus loss) Correlation

Again, APSC showed as significantly correlated to MPSC and CEER, as shown earlier. Thus, we removed APSC from the model. We included a pairs plot of retention status and several predictors in Appendix G.

2. Logit-link GLM and Stepwise Regression

- Note (1): The following results continue the GLM numbering pattern used from Retention Model 1.
- Note (2): Retention Model 2 attempts to predict the retention of USMA graduates after their initial five-year commitment. Because prior research suggests military officers make the decision to leave/ stay between their sixth and seventh year of service, we excluded USMA YG 2007 from this data set (see Table 5, section IIC).

We created our first GLM (GLM 4) using the logit link and compared it to the model generated by stepwise regression using ANOVA. Although the main effects model generated a lower residual deviance (from the ANOVA), we retained the stepwise model over it because it had a lower AIC. We compared a clog-log-link model (GLM 5, not shown) against the stepwise model, but we rejected it. The clog-log model performed inferior to the logit-link. Table 23 and 24 show the significant variables from the stepwise of GLM 4 and the ANOVA, respectively.

Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.547	0.454	1.204	0.228
babrIN	1.212	0.282	4.300	<.001
Null deviance: 1903.1 on 1411 degrees of freedom				
Residual deviance: 1795.1 on 1394 degrees of freedom				
AIC: 1831.1				

Table 23. Significant Retention Predictors, Stepwise GLM 4

1. Main Effects Model: status ~ typ.ath + m.degree + f.degree + cm2 + co2 + ch2 + ceer + pae + eas + aas + fas + mpsc + ppsc + babr					
2. Stepwise Model: status ~ typ.ath + aas + babr					
	Resid. Df	Resid. De	Df	Deviance	Pr(>Chi)
1	1381	1788.9			
2	1394	1795.1	-13.000	-6.238	0.937

Table 24. Main Effects and Stepwise GLM 4 ANOVA Results

Each model revealed the Infantry basic branch (babr) as the most significant predictor. However, the main effects model also showed the military police branch as significant. It is worth noting that, although not significant at the $p< 0.05$ level, both the main effects and stepwise models generated armor and engineer branches at $p<0.07$. All of these branches related positively to retention beyond one's active duty service obligation.

3. Generalized Models and Stepwise Regression

We attempted to create a third GLM, by first using a GAM to identify needed variable transformations. However, all partial residuals versus predictor plots appeared linearly. We included a plot of the basic branch partial versus residual plot in Figure 10.

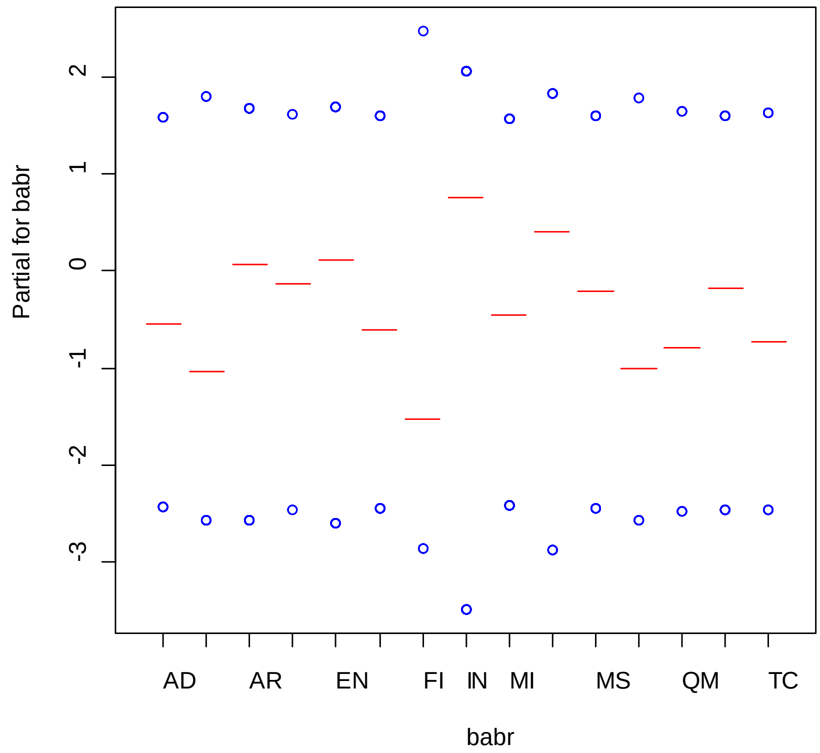

Figure 10.   Partial Residuals versus Predictor Plot, GAM

Using the summary output from Table 23, we constructed the fitted model. The fitted model, equation (2), shows infantry as the strongest indicator of retention.

$$\hat{\eta}_i = \hat{\beta}_0 + \hat{\beta}_1 X_1 + ... + \hat{\beta}_{p-1} X_{p-1}$$
$$\hat{\eta}_i = 0.547 + 1.212 X_{babr(INFANTYRY)}$$
$$\hat{\pi}_i = \frac{\exp(\hat{\eta}_i)}{1+\exp(\hat{\eta}_i)} = \hat{Y}_i \qquad (2)$$

4. Confusion Matrix, Retention Model 2

We used the following predicted probability threshold for our confusion matrix: $\hat{\pi}_i > 0.60$ retained (graduated), $\hat{\pi}_i \leq 0.60$ separated. This threshold maximized the correct classification rate and minimized the incorrect classification rate. Table 25 shows the confusion matrix for stepwise (GLM 4).

Raw Numbers		Observed Value	
		Active	Loss
Model Predicted	Active	507	337
	Loss	199	369

Percentages		Observed Value	
		Active	Loss
Model Predicted	Active	60%	40%
	Loss	35%	65%

Table 25. Active versus Loss Confusion Matrix

Our model classified 60 percent of those who remained on active duty correctly and classified 40 percent incorrectly. Furthermore, our model classified 65 percent of those who left active service (loss) correctly and 35 percent incorrectly. The model predicted the occurrence of loss five percent better than it did the occurrence of remaining on active duty.

5. Cross-validation Results

Using "R," we obtained a CV estimate of 39 percent, which signifies the percent of response variables we misclassified.

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DISCUSSION AND IMPLICATIONS

A. HARDINESS PREDICTION

Results from the first hardiness model indicated that less-educated but hard-working fathers (of males) and highly educated, hard-working mothers produce children higher in hardiness. We list a few preliminary results from hardiness model 1:

- Less-educated fathers of male cadets (interaction), educated mothers, public high schools, and private religious high schools relate positively to hardiness.
- Hardiness is unrelated to gender and CEER. Bartone et al. (2009) had similar findings and Matthews et al. (2000) state "…until stronger causal models have been developed, it seems safest to follow Halpern (1992) in supposing that sex differences in test performance may reflect a variety of interacting biological and cultural influences."

Although initial analyses (*N* = 3,716) found zero pre-admission predictors strongly related to hardiness, subsequent exploration of a second hardiness model revealed useful observations. First, hardiness model 2 revealed that less-educated mothers have a negative effect on the hardiness of cadet football players. This is consistent with the results from hardiness model 1, which suggested educated mothers have a positive effect on total hardiness. It is possible that a mother's victory over academic trials improves her son's ability to control outcomes and stay committed in the face of adversity.

Second, we see that liberal political views contribute little to total hardiness. It is not readily apparent as to why liberal football players have lower hardiness but we ascertain these cadets lack the commitment and control facets of hardiness needed to succeed at the academy. Further investigation revealed the tendency of liberals to be higher in hardiness-challenge (see Figure 11)[9]. It is possible that the negative coefficient estimate is associated with the liberal/ hardiness-challenge relationship.

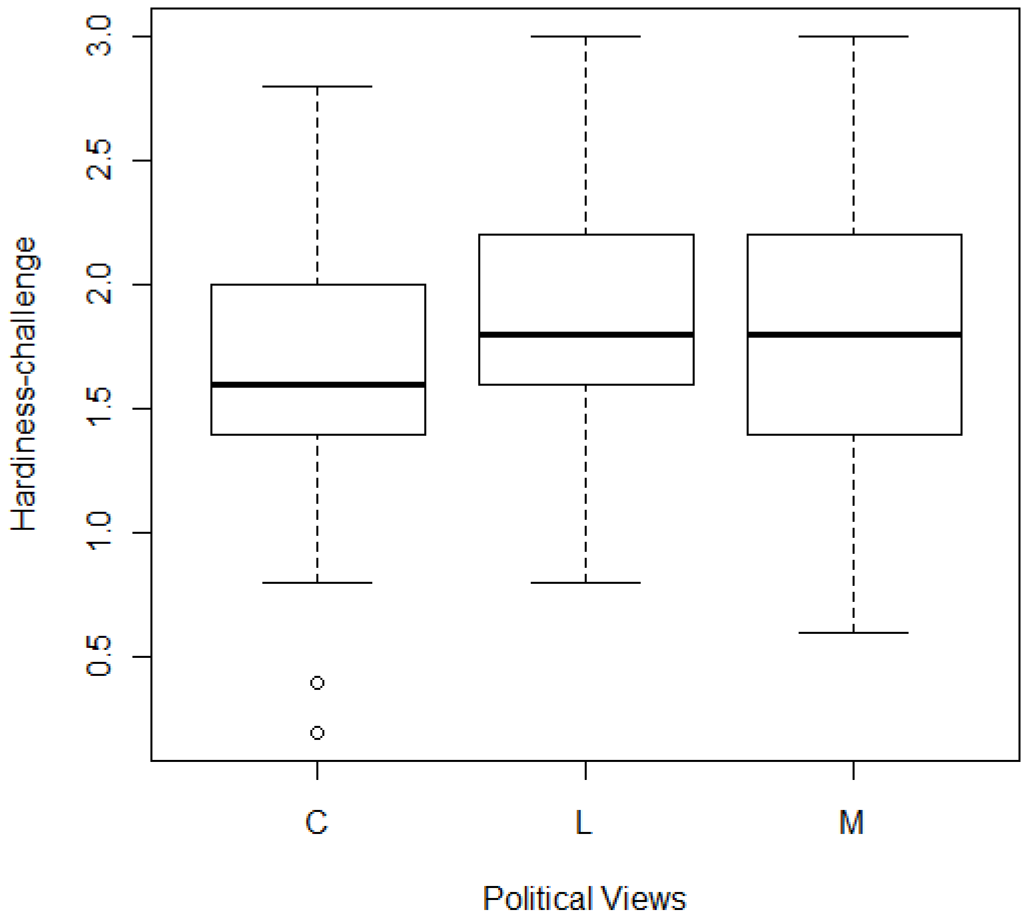

Figure 11. Hardiness-challenge versus Political Views

Third, the model suggests that the hardiness of cadet football players educated in the public school system remains unaffected by fathers' degree level. Since the majority of USMA cadets come from public schools, this finding

[9] Dots: outliers; top and bottom "T": Max/ min values, respectively; top and bottom of boxes: upper/ lower quartile (25 per cent of the data); dark horizontal line: median (50 percent of the data)

encourages us to inspect the hardiness of cadets from other high school types, namely, private religious high schools. It may be that educated fathers, who mask their detachment by enrolling their sons in private school, produce less hardy USMA cadets.

Next, we see from Figure 6 that USMAPS attendees with conservative political views exhibit lower average hardiness while politically liberal and moderate USMAPS attendees tend to possess greater hardiness.

Lastly, we comment on race. The summary output and interaction plot indicate African Americans with fathers who served in the military relate most to hardiness. Surely, there are societal and familial reasons why African Americans differ from Caucasians.

Although there are rules and regulations regarding the selection of candidates based on race, gender, etc., we recommend additional study of hardiness and race, in combination with other factors (e.g., parents' education level). Specifically, additional minority data would increase their sample size and perhaps reveal noteworthy findings.

B. PREDICTION OF RETENTION AT USMA

Results from the first retention (graduation versus separation) analysis show that academic scores (i.e., APSC[10], PPSC, and MPSC) relate to retention the most. Adequate academic, military and physical performance appears unattainable for most of the separated cadets. It suffices to say, separated cadets most likely encountered academic, military or physical trouble.

We expected a hardiness facet to show a strong relationship with retention much like its sister personality factor grit. However, hardiness-challenge, only moderately effective, emerged as the only significantly related (hardiness) facet.

[10] We mention APSC even though we did not include it in the model. Recall, APSC strongly correlated with MPSC and CEER. It does not take away the fact that academic performance is important to retention just because APSC is not in the final model. Perhaps Cadet Performance Score would be a likely alternative to use in place of MPSC, APSC, PPSC, and CEER.

The relationship between hardiness-challenge, academics performance and retention seems to support previous research from Bartone et al., (2013), who found a pattern suggesting cadets high in CEER[11] and hardiness-challenge perform worse in leadership tasks. We can conclude that the result of poor (leadership) performance is eventual separation from the Academy.

The absence of hardiness-commitment from the final model, although surprising, reveals that individuals "committed or vigorously engaged to work, life, others and activities…" possess limited potential for retention when academic proficiency is lacking. This may indicate that hardiness and retention relate most when those who possess academic ability above a certain threshold need an extra boost to perform.

By definition, hardiness-control "…urges a person to persevere so that his efforts influence events and outcomes" (Maddi et al., 2012). Hardiness-control seems to pick up where hardiness-commitment leaves off, taking a proactive and positive response to adversity. However, the absence of hardiness-control in the retention models reveals the power of tangible factors (i.e., academic letter grades) to play a stronger role in the retention outcome of USMA cadets over the internally driven hardiness. Perhaps hardiness becomes apparent in small numbers of the population who are on a "thin line" of failure and passing.

The presence of fathers' degree in the model indicates the negative influence on retention by an *external* (to the individual cadet) factor. We cannot ascertain why fathers' education level affects retention in this way; future study may shed light on this phenomenon.

Next, we identified two athletically related variables associated with retention. First, varsity athletes, among the most task-saturated of cadets at USMA, undergo various testing on and off the athletic field. Varsity athletes also travel across the country representing West Point on a weekly basis (during the

[11] Table 17 showed APSC highly correlated with CEER

academic year). However, it is not clear whether the negative effect from athlete type is due to the demands of the increased workload experienced during the academic year, the sport type, recruiting challenges (less than well-rounded cadets who are strong athletically but moderate or weak academically), or something else.

The presence of PAE in the model, although of small consequence, is interestingly one of indicators obtained by pre-admission testing. However, without further study we cannot accurately link PAE to retention.

Lastly, the misclassification rate produced by cross-validation indicates that our model attributes the amount of variation in the model to the chosen predictors 78 percent of the time.

C. U.S. ARMY RETENTION AND THE USMA GRADUATE

The retention model revealed a truth familiar to most post-GWOT Army officers, namely, that war affects infantry officers the most. That infantry officers are the first the raise their hand and depart from service, is perhaps a misconception. On the contrary, GLM 4 indicates the Infantry basic branch positively relates to active duty (retention).

Reasons why Infantry officers remain on active duty longer than their peers, although not investigated in the present work, no doubt include the ability to persevere through of a variety of work, family, and stress-related circumstances experienced from multiple deployments. Previous work (Britt et al., 2001) supports this finding and if we examine the lifestyle of the average U.S. Army Infantry officer "those engaged in meaningful work during the deployment, derive benefits months after…"

The Army utilizes the Infantry branch more frequently than any other branch in war situations. In fact, the other Army branches exist to support the Infantry. Hence, it is no surprise that those "engaged in work" possess greater potential for retention more than the less engaged. Infantry's sister "maneuver" branches (i.e., military police, armor, engineers[12]) also relate positively to retention, thus supporting this finding.

Variable	Estimate	Std. Error	z value	Pr(>|z|)	Branch Area
babrMP	0.847	0.444	1.909	0.056	MFE
babrEN	0.557	0.299	1.862	0.063	MFE
babrAR	0.500	0.290	1.726	0.084	MFE

Table 26. Maneuver Branches Positively Related to Retention

Lastly, the misclassification rate indicates our model predicts the correct retention response 61 percent of the time.

D. CONCLUSIONS AND FUTURE WORK

1. Pre-admission Predictors of Hardiness

The power of hardiness to predict performance across multiple contexts inspires further exploration of a hardiness predictor among pre-admission variables and across various groups. The hardiness subset of football players revealed the power of linear regression to develop a hardiness predictor in a target population. We recommend investigating the target group(s) hardiness is best predictive for and why. For example, is hardiness most predictive in varsity athletes or non-varsity athletes?

Additionally, the significance of race in the model is suggests that hardiness differs by race, even when other factors are held constant. We recommend further exploration to determine which factors influence hardiness in each race. Results may influence training and faculty development at USMA.

[12] Although the armor and engineer branches were not significant at the $p<.05$ level, we included them in Table 26 to show their positive coefficient estimates and communicate how close their p-values came to 0.05.

Lastly, we recommend the development of pre-admission hardiness predictor using the ideas mentioned above as a contextual framework. We could utilize USMA's current hardiness battery to develop additional guideposts that aid the USMA admissions committee in assessing a candidate's future hardiness. From the battery, we can identify corresponding activities, scores, etc., obtained during high school. Either the hardiness predictor, along with other metrics, might comprise a revised WCS or it may serve as a stand-alone "hardiness predictor" score.

2. USMA Predictors of U.S. Army Leader Performance

Measuring true leader performance is often confusing and subjective, leaving detached superiors to rate their subordinate leaders. The U.S. Army is no different. The 2009 article by Bartone et al., investigated the most predictive attributes of leader performance while at USMA. We extend the work started by these researchers by encompassing leader performance in the U.S. Army. Leader performance at USMA should be a stepping-stone goal to performing well as a military officer. We can also tie in hardiness to discover its relationship to officer evaluations and promotion.

3. Demographics, Parents' Education and USMA Retention

Father's degree relates negatively to retention when the level attained is high school but, by how much? The coefficient estimate, $\beta_{\text{f.degree (HS)}} = -0.296$ is low (less than 1.0). Further investigation may prove beneficial, especially in light of the relationship between father's degree (high school) and male cadets. Additionally, future study could identify the effect a father's degree (high school) has on other demographics (i.e., race) to discover, for example, if minority retention differs from the majority.

4. Retention of USMA Graduates in the U.S. Army

The lack in predictive power of the retention model suggests that we need additional research. Every year USMA's assessment steering committee (ASC) contacts many U.S. Army supervisors and raters of USMA graduates. ASC's goal is to determine if the customer (U.S. Army) is satisfied with their product (USMA graduate/ second lieutenant). New to this discussion are a USMA graduate's reason(s) for leaving active federal service (i.e., whether the product is satisfied with the customer). Retention research (Gjurich, 1999) for junior surface warfare officers found the amount of time spent on sea duty, the perceived probability of finding a civilian job, satisfaction with pay and allowances, satisfaction with current military job, satisfaction with job training, and satisfaction with working conditions as most influential of a career decision to remain in service beyond their initial obligation. For U.S. Army officers, we recommend the investigation of similar factors, namely, the ratio of deployment/ non-deployment time, perception of the economy and probability of finding a civilian job, satisfaction with pay, job, etc.

Future research may guide the development and issuance of a questionnaire by ASC for officers released from active federal service. The goal is to identify additional predictors of retention—USMA could use the predictors to enhance curriculum, policy, selection and training.

5. MacArthur's Proclamation: Athletes and Leadership

Among other things, we remember General Douglas MacArthur for his decision to place special emphasis on athletics at USMA. He believed athletes made the best leaders because sports situations mimicked in the field of war. Future research should include the role of athletics at USMA and beyond. The study would seek to investigate MacArthur's assertion that athletes make the best leaders. Because all USMA cadets participate in athletics, the study would distinguish between intramural, club and varsity (intercollegiate) athletes and evaluate their U.S. Army military performance and retention.

APPENDIX A. GLOSSARY

Athletic Activities Score (AAS): A score reflecting a candidate's athletic participation awarded in accordance with guidelines established by USMA admissions department. See Appendix B for additional explanation.

Captains Career Course (CCC): U.S. Army school designed for preparing company level officers to command, staff, and manage operations at the operation unit level. The course scope includes training instruction and practical exercises in Army operations, professional military topics in common functional areas, unit leadership, doctrinal base, tactical decision making, maintenance and logistics, and military writing (USACAC, 2013).

Community Leadership Score (CLS): A score composed of the sum of a USMA candidate's AAS, EAS and FAS, divided by three. See Appendix B for additional explanation.

Corps Squad Athlete: West Point intercollegiate sports athlete

Extracurricular Activities Score (EAS): A score reflecting a candidate's participation in activities outside required school curricula awarded in accordance with the guidelines established by USMA Admissions Department. See Appendix B for additional explanation.

Faculty Appraisal Score (FAS): The average candidate scores on the school official evaluation (SOE) of candidate forms (DD Form 1869) on a scale of 40/740. See Appendix B for additional explanation.

Firstie: A member of West Point's senior class.

Intermediate Level Education (ILE): The purpose of the Army's ILE program is to provide all mid-grade officers a basic foundation of professional military education and leader development training. It develops leaders prepared to execute full spectrum operations; trains and educates leaders in the practice and values of the profession of arms; and prepares leaders to operate in joint, multi-national and interagency environments. ILE prepares officers for duty as field grade commanders and staff officers throughout the Army, primarily at brigade and higher echelons (HRC, 2013).

Physical Assessment Exam Score (PAE): A score achieved by a USMA candidate upon successful completion of the basketball throw, pull-ups (or flexed-arm hang for women), standing long jump and the 300-yard shuttle run. Recently revised and replaced by the candidate fitness assessment (CFA), a pre-admission assessment also used by the U.S. Naval Academy and U.S. Air Force Academy.

Plebe: A member of West Point's freshman class.

APPENDIX B. USMA ADMISSIONS FILE CALCULATIONS

(Taken from Class of 2000 WCS Calculations Sheet and from a USMA Admissions document entitled "Annex A: Quantification of Candidate File Components")

WHOLE CANDIDATE SCORE (WCS)
WCS: (6 x CEER) + (3 x CLS) + (PAE SCORE)

COLLEGE ENTRANCE EQUIVALENCE SCORE (SCHOLASTIC APTITUDE TEST, "SAT")
CEER: (.364 x HSR) + (.269 x SATV) + (.432 x SATM) - 48

COLLEGE ENTRANCE EQUIVALENCE SCORE (AMERICAN COLLEGE TEST, "ACT")
ACEER: (.219 x HSR) + (9.43 x ACTM) + (4.62 x ACTE) + (0.45 x ACTS) + (4.01 x ACTR) - 41.5

HIGH SCHOOL RANK (HSR)
HSR: ((2 x HS·STANDING) -1) / (2 x CLASS SIZE);
*HSR TABLE REQUIRED TO CONVERT CALCULATED RESULT TO HSR SCORE

COMMUNITY LEADER SCORE (CLS)
CLS: (EX+ AT+ FAS) / 3

EXTRACURRICULAR ACTIVITIES SCORE (EX): A score reflecting a candidate's participation in activities outside required school curricula awarded in accordance with the following guidelines:

800: An outstanding young person with quadruple participation or honors and awards on selected extracurricular activities (each worth 600 or more points).

700:
(1) Student Council President;
(2) Triple participation or honors and awards in selected extracurricular activities (each worth 600 points);
(3) Participation in Boys/Girls Nation;
(4) JROTC Regimental/Brigade Commander or Civil Air Patrol Spaatz Award winner;
(5) Decoration for valor [Soldiers];
(6) Ranger or Special Forces tab [Soldiers].

600:
(1) High-school Class President;
(2) Editor-in-chief of a school publication;
(3) Participation in Boys/Girls State, President of National Honor Society, or recipient of a National or State award;
(4) Eagle Scout (Boy Scouts) or Gold Award (Girl Scouts);
(5) Triple participation or honors and awards in selected extracurricular activities (each worth 500 points)
(6) Earhart/ Mitchell Award;
(7) Combat Infantryman Badge; Combat Action Badge; Combat Medical Badge [Soldiers];
(8) Soldier's Medal [Soldiers];
(9) Soldier of the Year-brigade-level or higher [Soldiers];
(10) Division-level In-Service Recruiting Program [Soldiers].

500:
(1) Holder of one or more elective offices in moderately selective organizations;
(2) Participation in activities or recipient of awards in moderately selective organizations;
(3) Holder of a private pilot's license;
(4) EMT/EMS or Volunteer Firefighter;
(5) National Honor Society VP/Treasurer or Secretary;
(6) Civil Air Patrol officer/ 1SG;
(7) Combat veteran of three or more months in theater [Soldiers];
(8) Expert Infantryman Badge or Expert Field Medical Badge [Soldiers];
(9) Meritorious Service Medal [Soldiers];
(10) Distinguished Honor Graduate of Army school [Soldier];
(11) Soldier of the Quarter—brigade-level or higher [Soldiers].

400:
(1) Participation in activities or recipient of awards in organizations with limited selectivity;
(2) Non-commissioned officer (Soldiers];
(3) Squad Leader or Platoon Guide [Soldiers];
(4) 90-day-plus OCONUS tour [Soldiers];
(5) Army Commendation Medal [Soldiers];
(6) Master Fitness Trainer [Soldiers];
(7) Honor Graduate of an Army school [Soldiers];
(8) PLDC graduate [Soldiers];
(9) BOSS Representative [Soldiers].

300:
(1) Some participation in organized activities;
(2) Army Achievement Medal or Good Conduct Medal [Soldiers].

200: No participation in organized activities.

ATHLETIC ACTIVITIES SCORE (AT): A score reflecting a candidate's athletic participation awarded in accordance with the following guidelines:

800: An outstanding athlete (All-American, First team All-Area selection in baseball/softball, basketball or football) and either Athletic rating of 1 or 2 in the sport in which honors are received or CFA score > 650.

700:
(1) First-team All-Area selection in a single sport (other than baseball/softball, basketball or football);
(2) Captain of baseball/softball, basketball, or football team;
(3) Team captain in two or more sports (other than baseball/softball, basketball or football) for class size over 100); and
(4) Ranger or Special Forces tab [Soldiers].

600:
(1) Captain of team (other than baseball/softball, basketball, or football);
(2) Varsity letter in baseba11/softba11, basketball, or football; and
(3) Varsity letter in two or more sports (other than baseball/softball, basketball, or football).

500:
(1) Varsity letter in a single sport (other than baseball/softball, basketball, or football); and
(2) Expert Infantryman Badge, Expert Field Medical Badge, Jumpmaster, or Presidential Fitness award [Soldiers].

400:
(1) Participation in a varsity sport (no letter);
(2) Graduate of Airborne, Air Assault, Pathfinder, or comparable other _Army school [Soldiers]; and
(3) Maximum score on Army Physical Fitness Test [Soldiers].

300:
(1) Participation in junior-varsity and other team sports (not intramurals); and
(2) Soldier status.

200: No participation and no evidence of interest in sports.

FACULTY APPRAISAL SCORE (FAS): The average of the candidate's scores on the School Official Evaluation (SOE) of Candidate Forms (DD Form 1869) on a scale of 40 740.

NOTE: The information above contains general guidance on the components used to compute a Community Leader Score (CLS). In a process as imprecise as leadership assessment, subjective judgment must be applied to the evaluation process in order to take into consideration special situations: e.g., an unusually high or low Faculty Appraisal Score (FAS) that is inconsistent with other elements of the candidate record; athletic achievement in an extremely large or small school or an excellent or marginal program; an activity record that may not fit the categorizations of the Candidate Activities Record. The Admissions Office and the Admissions Committee are expected to make adjustments in the components of the CLS to take into account such situations.

APS: (.001926 x HSR) + (.002283 x SATM) + (.001421 x SATV) - .6865

HPA NEW SAT: (.001070 x SATM) + (.003462 x SATV) + (.002035 x HSR) - 1.390

HPA ACT: (.001249 x HSR) + (.04132 x ACTE) + (.01087 x ACTM) + (.02944 x ACTSR) - .3257

MSE NEW SAT: (.004884 x SATM) - (.000093 x SATV) + (.002477 x HRS) -1.652

MSE ACT: (.002004 x HSR) + (.1487 x ACT.M) + (.03713 x ACTSR) • (.02022 x ACTR) - (.06084 x ACTM(GT)) - 2.2873

RISK LEVELS AND REQUIRED CHECKS:

SATV	<560
SATM	<560
ACTE	<23
ACTM	<24
ACTR	<24
ACTS	<23
CEER/ ACEER	<520
CLS	<450
PAE	<420
FAS	<525
WCS	<5200
HPA	<2.10
MSE	<2.10
APS	<2.15

DEFINITIONS:

LEADER: CLS $\geq$ 650
SCHOLAR: CEER OR ACEER $\geq$ 650

ESTIMATES:
FAS = 600
P AE = (AT + 400)/2

APPENDIX C. ORIGINAL VARIABLES

	Variable Name (42)		Variable Type	Levels	Range (min,max)	Hardiness	Retention #1	Retention #2
1	Gender of the Cadet		CN	2		★		
2	Racial/ Ethnic Descent category		CN	7		★		
3	Parent Graduated USMA		CN	4		★		
4	Parent with Service		CN	4		★		
5	Father's Career	[*]	CN	47		★	★	★
6	Mother's Career	[*]	CN	47		★	★	★
7	Type of High School Attended	[**]	CN	8		★		
8	Recruited Athlete		CN	2		★		
9	Political Orientation		CO	6		★		
10	USMA Prep School Graduate		CN	2		★		
11	College Entrance Equivalence Rating		QI		(407, 800)	★	★	★
12	Extracurricular Activities Score		QI		(200, 800)	★	★	★
13	Athletic Activities Score		QI		(200, 800)	★	★	★
14	Faculty Appraisal Score		QI		(0, 740)	★	★	★
15	Physical Aptitude Exam Score		QI		(0, 800)	★	★	★
16	Total Hardiness Score		N		(0.53, 3.0)	★		
17	Hardiness Challenge		N		(0, 3.0)		★	★
18	Hardiness Commitment		N		(0.6, 3.0)		★	★
19	Hardiness Control		N		(0.4, 3.0)		★	★
20	Academic Program Score		N		(0.00, 4.22)		★	★
21	Military Program Score		N		(0.429, 4.188)		★	★
22	Physical Program Score		N		(0.00, 4.179)		★	★
23	Competitive Club Sport	[#]	CN	29			★	★
24	USMA Status Code		CN	2			★	
25	Basic Banch		CN	19				★
26	Active Duty Status		CN	2				★
27	Personal Identification Number (Pin ID)		CN	3716				
28	Class Admitted to		CN	3				
29	Class Year of Record		CN	6				
30	Graduation Date from USMA		CN	19				
31	Commissioning Date from USMA		CN	19				
32	Recruited Athlete Rating Code		CO	6				
33	Sport Recruited for		CN	21				
34	Corps Squad Sport	[#][***]	CN	27		★	★	★
35	Whole Candidate Score		QI		(4698, 7331)			
36	Community Leadership Score		QI		(418, 775)			
37	Cadet Performance Score		N		(0, 3.9)			
38	Academic Quality Point Average		N		(.458, 4.198)			
39	Date of Loss to USMA		CN	483				
40	Date of Loss Active Duty		CN	279				
41	Years of Service as of 31 JAN 2013		N		(0, 7.80)			
42	Rank on Active Duty		CO	3				

[*] Used to create variables **f.degree** & **m.degree**, denoting the education level needed for parents' career type
[**] 73 "NA" values were imputed "public, the average type of high school
[***] Used to creat variable **playedsport1**, denoting whether a cadet played an intercollegiate sport or not
[#] Used to create the variable **type.ath**, denoting competitive sport type (i.e., intramural, club, varsity)
CN Categorical, Nominal
CO Categorical, Ordinal
QI Quantitative, Integer
N Continuous, Numeric

Table 27. Hardiness and Retention Variables

Explanations of the variables should be self-evident; however, we describe extracurricular activity, faculty appraisal, athletic activity, physical assessment exam and community leadership scores in the glossary (Appendix A).

OIR also released variables, not included above, useful for identification purposes. To comply with human subjects research restrictions, we used the PIN variable to assign a pseudo name to each data entry. This prevented the divulging of personally identifying information. “Class admitted to” and “class year of record” are redundant variables previously used to identify year groups. “Date of loss” (to USMA), “commissioning date” (from USMA), and “date of loss” (while on active duty) variables indicated when a cadet departed West Point, commissioned in the U.S. Army, and departed the U.S. Army active duty service, respectively. “Active duty status” and “rank” (on active duty) indicated whether the USMA graduate remained in the Army or not, and their current, or attained rank.

A. VARIABLES NOT USED IN THE ANALYSIS:

We did not use “class year of record” (not shown) in this analysis due to redundancy. Few entries had differing years for “class year of record” and “class admitted to.”

“Date of loss” (to USMA) and “date of loss” (while on active duty), (neither shown) were not used in this analysis due to redundancy or lack of need. Dates were not of particular interest to this project; rather, the occurrence of the outcome (i.e., loss) proved beneficial. USMA “graduation status” (whether a cadet graduated or separated) and “active duty status” deemed sufficient to address the retention research question.

“Commissioning date” and “graduation date,” (neither shown) did not appear to differ from each other except in a fraction of cases. We discarded the noted cases from the final data set.

Lastly, we did not use “rank” (not shown) in the analysis. Rank attained between the sixth and eighth year of service for most Army officers in a particular year group remained the same (captain). There are exceptions (e.g., officers branched into the medical field to serve as doctors or those who did not receive promotion for disciplinary reasons). We show the initial groupings of original variables into data sets below (Table 30). Appendix D contains sample images, in spreadsheet form, of the data sets.

Group 1: Hardiness Predictor	
Outcome (Dependent) Variables	
Hardiness – Commitment	Hardiness – Control
Hardiness – Challenge	Hardiness – Total
Predictor (Independent) Variables	
Gender	Race
Father's Career	Mother's Career
Political View	Parent USMA Graduate
Parent Uniformed Service	Type of High School Attended
Whole Candidate Score	College Entrance Equivalency Rating
Physical Assessment Exam Score	Community Leadership Score
Extracurricular Activity Score	Athletic Activity Score
Faculty Appraisal Score	USMA Prep School Attendee
Recruited Athlete	Sport Recruited For
Recruited Player Rating	
Group 2: Retention	
Outcome (Dependent) Variables	
USMA Graduation Status	Years of Services (U.S. Army Officer)
Predictor (Independent) Variables	
Hardiness – Commitment	Hardiness – Control
Hardiness – Challenge	Hardiness – Total
Cadet Academic Quality Point Average	Cumulative Academic Program Score
Cumulative Military Program Score	Cumulative Physical Program Score
Cumulative Cadet Performance Score	Corps Squad Sport Played
Club Squad Sport Played	Basic Branch
Identifier Variables:	
Personal Identification (PIN)	Class admitted to
Active Duty Status	

Table 28. Original 42 Variables

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APPENDIX D. SAMPLE DATA SETS

A. SAMPLE HARDINESS DATA SET

pn_id	clapplyto	usma_stat_cd	gender	race	usmaps	recath2	playedsport1	wcs	ceer	pae	cls	eas	aas	fas	f.degree	m.degree	poliview	pGrad	pServ	typehs	hrdns2
C718	2005	S	Male	Cauc	No	0	0	5931	608	486	599	500	600	698	High	HighSchool	C	Neit	Father	Home	1.53
C147	2007	G	Male	Cauc	No	0	0	5291	526	518	539	500	400	718	Colle	HighSchool	C	Neit	Neither	Home	1.73
C523	2005	G	Male	Cauc	No	0	0	6183	608	612	641	500	700	723	High	College	C	Neit	Father	Priva	1.73
C171	2007	G	Male	Cauc	No	0	0	6059	620	623	572	500	500	715	Colle	HighSchool	M	Neit	Neither	Home	1.8
C389	2007	G	Male	Cauc	No	1	1	6071	616	539	612	400	700	737	Grad	HighSchool	C	Neit	Father	Home	1.8
C515	2005	G	Male	Cauc	No	1	1	5684	521	644	638	400	800	714	High	GradSchool	C	Neit	Neither	Home	1.8
C932	2005	G	Male	Cauc	No	0	0	6161	650	626	545	400	500	734	Colle	HighSchool	FR	Neit	Neither	Home	1.87
C682	2005	G	Male	Cauc	No	0	0	6386	733	458	510	500	300	729	Colle	HighSchool	C	Neit	Father	Priva	1.93
C942	2006	G	Male	Cauc	No	0	0	5945	591	500	633	600	600	698	High	College	C	Neit	Neither	Home	1.93
C716	2006	G	Male	Cauc	No	1	1	6354	639	588	644	400	800	732	Colle	HighSchool	C	Neit	Neither	Home	1.93
C349	2005	G	Male	Cauc	No	0	0	5277	509	612	537	300	600	712	High	HighSchool	C	Fath	Both	Home	1.93
C981	2007	S	Fema	Cauc	No	1	1	6018	647	510	542	400	500	726	High	HighSchool	C	Neit	Neither	Publi	2
C990	2007	G	Male	Cauc	No	1	1	6692	649	662	712	700	700	737	Grad	College	C	Neit	Neither	Home	2
C560	2006	S	Male	Cauc	No	1	1	5814	585	588	572	300	700	715	High	HighSchool	C	Neit	Neither	Home	2.07
C815	2006	G	Male	Af.Am	Yes	0	0	5387	489	518	645	600	600	735	Colle	HighSchool	C	Neit	Both	Publi	2.07
C975	2007	G	Male	Asian	No	0	0	5738	571	581	577	500	500	732	High	HighSchool	C	Neit	Neither	Home	2.13
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	.																		.		

Table 29. Hardiness Data Set

B. PARENTS' DEGREE BREAKDOWN BY CAREER

HighSchool	College	GradSchool
Homemaker	Teacher-elementary	College teacher
Other	Teacher-secondary	Business executive
Undecided	Business owner	Therapist
Unemployed	Nurse	Physician
Farmer/Rancher	School counselor	Clergy
Business clerk	Social worker	Policy/Govt
Semi-skilled	Business sales	Optometrist
Law enforcement	Accountant	Dentist
Skilled trades	Military science	Psychologist
Laborer	Programmer	Veterinarian
Lab technician	Pharmacist	Science researcher
Interior Decorator	Dietitian	Other religious
College admin	Lawyer	
Artist	Writer	
	Actor	
	School principal	
	Engineer	
	Architect	
	Musician	
	Foreign service	
	Conservationist	

Table 30. Parents' Degree Breakdown by Career Type

C. SAMPLE RETENTION DATA SET, GRADUATION VERSUS SEPARATION

pn_id	clapplyto	ath.Varsity	ath.Club	typ.ath	cm2	co2	ch2	hrdns2	caqpa	apsc	mpsc	ppsc	cpsc	status
C00006077	2005	0	1	Club	2	2.4	2.4	2.27	2.147	2.1	2.225	2.602	1.968	1
C00033306	2005	1	0	Var	2.2	2.6	2.2	2.33	2.694	2.64	3.103	3.44	2.752	1
C00039684	2007	0	0	IM	2.8	2.6	2.2	2.53	3.286	3.309	2.945	2.587	2.938	0
C00088100	2005	0	0	IM	2.2	2	1.8	2	3.077	3.064	2.475	3.194	2.709	1
C00138788	2006	0	0	IM	1.8	1.8	1.6	1.73	3.378	3.391	2.869	3.133	3	1
C00153993	2005	0	0	IM	2.2	1.4	2.8	2.13	2.601	2.58	2.47	2.48	2.29	1
C00195017	2006	0	0	IM	1.8	2.2	2	2	2.195	2.158	2.654	2.688	2.153	1
C00202724	2006	0	1	Club	2.4	1.8	1.6	1.93	2.675	2.654	2.72	2.846	2.483	1
C00248021	2007	0	1	Club	1.6	2.4	2	2	2.749	2.736	2.716	2.78	2.466	1
C00271310	2005	1	0	Var	2.4	2	1.8	2.07	2.814	2.798	2.327	3.352	2.545	1
C00272553	2007	0	0	IM	2.4	2.8	2.4	2.53	2.934	2.898	2.941	3.374	2.77	1
C00308170	2005	1	0	Var	2	2	1	1.67	3.748	3.773	2.901	3.061	3.218	1
C00325548	2006	0	0	IM	2.2	2.2	2.2	2.2	2.892	2.888	2.672	2.786	2.585	1
C00378676	2006	0	0	IM	1.8	2.2	0.8	1.6	2.835	2.833	1.754	1.884	2.069	0
C00392880	2007	0	0	IM	2	2	1.8	1.93	2.639	2.615	2.621	3.154	2.443	1
C00433896	2007	1	0	Var	2.8	2.8	1.6	2.4	3.418	3.419	2.766	3.008	2.935	1
	.											.		
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	.											.		

Table 31. Retention Data Set 1, Graduation versus Separation Status

D. SAMPLE RETENTION DATA SET, ACTIVE DUTY VERSUS LOSS

pn_id	clapplyto	ath.Varsity	ath.Club	cm2	co2	ch2	hrdns2	caqpa	apsc	mpsc	ppsc	cpsc	babr	usma_stat_cd	status
C77384895	2006	0	0	1.8	1.8	1.6	1.73	2.187	2.16	2.096	2.364	1.904	AD	G	ACTV
C45728430	2006	0	0	1.8	1.8	2.2	1.93	2.246	2.205	2.077	2.608	1.971	AD	G	ACTV
C45498479	2006	0	0	2.8	2.8	3	2.87	2.143	2.131	2.269	2.566	1.986	AD	G	ACTV
C49265657	2006	1	0	1.6	2	1.6	1.73	2.038	2.015	2.536	2.654	2.028	AD	G	ACTV
C05375855	2005	0	0	1.6	0.8	2	1.47	2.236	2.183	2.22	2.772	2.048	AD	G	ACTV
C77784951	2005	0	0	2.4	2.4	1.6	2.13	2.32	2.295	2.184	2.575	2.054	AD	G	ACTV
C82222947	2005	1	0	2.2	1.8	1.8	1.93	2.072	2.023	2.419	2.885	2.055	AD	G	ACTV
C21415381	2005	0	1	1.6	1.4	2	1.67	2.229	2.162	2.717	2.289	2.109	AD	G	ACTV
C43071104	2006	1	0	2	1.8	1.8	1.87	2.278	2.21	2.185	3.264	2.141	AD	G	ACTV
C93445499	2005	1	0	2.2	2.2	1.8	2.07	2.411	2.372	2.198	2.877	2.165	AD	G	ACTV
C41556663	2007	1	0	2.4	2.2	2.8	2.47	2.465	2.463	2.271	2.885	2.172	AD	G	ACTV
C58475599	2006	0	0	2.6	2.8	2	2.47	2.27	2.23	2.376	3.071	2.177	AD	G	ACTV
C28336741	2005	1	0	2.2	1.8	2	2	2.146	2.086	2.347	3.418	2.178	AD	G	ACTV
C00888679	2005	0	0	2.2	1.6	1.8	1.87	2.244	2.183	2.812	2.421	2.182	AD	G	ACTV
C97492056	2007	0	0	2.4	2.2	2	2.2	2.534	2.52	2.431	2.543	2.192	AD	G	ACTV
C63873235	2007	1	0	1.4	2	2.2	1.87	2.311	2.256	2.72	2.855	2.208	AD	G	ACTV
C22838372	2006	1	0	2.8	2.4	1.2	2.13	2.315	2.279	2.498	2.923	2.216	AD	G	ACTV
C67141596	2005	0	0	2.4	2.2	2.4	2.33	2.305	2.251	2.767	2.54	2.229	AD	G	ACTV
C38313510	2007	0	1	2	2.2	1.6	1.93	2.448	2.438	2.67	2.555	2.234	AD	G	ACTV
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	.											.			
	.											.			

Table 32. Retention Data Set 2, Active Duty versus Loss Status

APPENDIX E. SIMPLE LINEAR REGRESSION APPROACH EXPLAINED

A. HARDINESS AND SIMPLE LINEAR REGRESSION

Mathematical formulation came from Kutner, Nachtsheim, Neter, & Li (2005).

After an examining the data, we used regression analysis to explain the relationship between the chosen predictors and outcome (also called *criterion* or *response*) variables. Generally, the outcome variable we wish to predict, denoted *Y*, is the *dependent variable*. The predictor, denoted *X*, is referred to as the *independent variable*. We relate *Y* and *X* as follows:

$$Y = f(X) \tag{3}$$

Outcome and predictor variables never relate perfectly, but the aim is to find the tendency of an outcome for *Y* to vary with the predictor variable *X*. We see the imperfect relationship by plotting the two variables in a space containing an *X*-axis and *Y*-axis and drawing a best-fit line. On either side of the line are scatter points. The distance from each point to the fitted line is called the error term Epsilon ("ε"). ε accounts for randomness and captures the variability in the outcome unexplained by the predictors (Montgomery et al., 2001). The introduction of error changes our function to the following:

$$Y = f(X) + \varepsilon \tag{4}$$

Additionally, there is a probability distribution of *Y* for each level of *X*. A probability distribution assigned a probability to each outcome. Often, regression models require more than one predictor. The addition of other predictors changes our best-fit line to a best-fit surface (e.g., a planar surface with two predictors, X_1 and X_2). The functional equation then becomes:

$$Y = f(X_1, X_2, ..., X_n) + \varepsilon \tag{5}$$

One of the challenges in designing a regression model is to determine which predictors X_i, $i=1,\dots,n$ are to be used and which should be discarded. A second challenge is finding an appropriate functional form of the model. Two common functional forms are linear and quadratic models. The most common form is a regression model in which the regression relation is linear. The general form follows:

- One variable

$$f(X) = \beta_0 + \beta_1 X_i,$$
$$Y = f(X) + \varepsilon, \tag{6}$$
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

- Two or more variables

$$f(X_1, X_2, \dots, X_n) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_n X_{ni}$$
$$Y = f(X_1, X_2, \dots, X_n) + \varepsilon,$$
$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_n X_{ni} + \varepsilon_i \tag{7}$$

where:

- Y_i is the regression function's outcome at the i^{th} trial (for the i^{th} participant)
- β_0 is the Y intercept of the regression line
- β_1 is the slope of the regression line
- X_i is the predictor value at the ith trial (for the i^{th} participant)
- X_{ni} is the nth predictor value at the ith trial (for the i^{th} participant)
- ε_i is a random error term is mean $E\{\varepsilon_i\}=0$ and variance $\sigma^2\{\varepsilon_i\}=\sigma^2$
- Note: β's are also called regression coefficients or parameters
- X_0, although not shown is equal to 1 and is paired with β_0; $\beta_0 X_0 = \beta_0(1) = \beta_0$

When there is only one predictor and the regression coefficients and predictors are linear (non-exponential, non-multiplicative, etc.), it is a simple linear regression model.

We may show all *i* (1 through *n*) observations of our regression model using the following matrix representation:

$$Y_i = X\beta_i + \varepsilon_i,\ i = 1 \ldots n \tag{8}$$

where $\mathbf{Y}$, $\boldsymbol{\beta}$, and $\boldsymbol{\varepsilon}$ are vectors of responses, parameters, and normal, random errors, respectively. $\mathbf{X}$ is a matrix of constants.

$$\underset{n\,x\,1}{\mathrm{Y}} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} \qquad \underset{n\,x\,p}{\mathrm{X}} = \begin{bmatrix} 1 & X_{11} & X_{12} \cdots X_{1,p-1} \\ 1 & X_{21} & X_{22} \cdots X_{2,p-1} \\ \vdots & \vdots & \vdots \ \cdots \ \vdots \\ 1 & X_{n1} & X_{n2} \cdots X_{n,p-1} \end{bmatrix} \qquad \underset{p\,x\,1}{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix} \qquad \underset{n\,x\,1}{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{9}$$

For visualization purposes, we substitute the actual (text) names for the real response and predictors for the hardiness (“H” below) model in equation (10).

$$\underset{n\,x\,1}{\begin{bmatrix} H_1 \\ H_2 \\ \vdots \\ H_n \end{bmatrix}} = \underset{n\,x\,p}{\begin{bmatrix} 1 & X_{1,Gender} & X_{1,Race} \cdots X_{1,Phys.Aptd.Score} \\ 1 & X_{2,Gender} & X_{2,Race} \cdots X_{2,Phys.Aptd.Score} \\ \vdots & \vdots & \vdots \ \cdots \ \vdots \\ 1 & X_{n,Gender} & X_{n,Race} \cdots X_{n,Phys.Aptd.Score} \end{bmatrix}} \underset{p\,x\,1}{\begin{bmatrix} \beta_0 \\ \beta_{Gender} \\ \vdots \\ \beta_{Phys.Aptd.Score} \end{bmatrix}} + \underset{n\,x\,1}{\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}} \tag{10}$$

Reverting to the previous notation using *X*s and *Y*s, we use matrix multiplication and addition to obtain a linear system of equations.

$$\underset{n\,x\,1}{\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}} = \underset{n\,x\,p}{\begin{bmatrix} 1 & X_{11} & X_{12} \cdots X_{1,p-1} \\ 1 & X_{21} & X_{22} \cdots X_{2,p-1} \\ \vdots & \vdots & \vdots \ \cdots \ \vdots \\ 1 & X_{n1} & X_{n2} \cdots X_{n,p-1} \end{bmatrix}} \underset{p\,x\,1}{\begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix}} + \underset{n\,x\,1}{\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}} \tag{11a}$$

$$= \underset{n\,x\,1}{\begin{bmatrix} \beta_0 + \beta_1 X_{11} + \cdots + \beta_{p-1} X_{1,p-1} \\ \vdots \\ \beta_0 + \beta_1 X_{n1} + \cdots + \beta_{p-1} X_{n,p-1} \end{bmatrix}} + \underset{n\,x\,1}{\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}} \tag{11b}$$

$$= \underset{n x 1}{\begin{bmatrix} \beta_0 + \beta_1 X_{11} + \cdots + \beta_{p-1} X_{1,p-1} + \varepsilon_1 \\ \vdots \\ \beta_0 + \beta_1 X_{n1} + \cdots + \beta_{p-1} X_{n,p-1} + \varepsilon_n \end{bmatrix}} \tag{11c}$$

We see multiple versions of equation (7) as the system of equations in matrix form (equation 11a, b, and c). The known values in most regressions are the *Y*s and the *X*s. One of the key points of regression is estimating the beta values in such a way that the right hand side equation (*X*s, beta's, error) is close to the left hand side (*Y*s). The most popular way of finding good estimates is by using the ordinary least squares method.

B. ORDINARY LEAST SQUARES

Simple linear regression (SLR) finds the optimal solution to the value of the regression coefficients (β) that minimizes the sum of squares error for a given set of *X*s and *Y*s using the ordinary least squares (OLS) method. OLS starts with an equation and impose a restriction that the sum of errors is zero between the actual response and the expected value of the response, denoted $E[Y_i]$.

$$E[Y_i] = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_n X_{ni} \tag{12}$$

With the errors equal to zero, take the difference between the actual response and the expected value and solve for the beta values.

$$Y_i = E[Y_i] \rightarrow Y_i - E[Y_i] = 0$$
$$Y_i - (\beta_0 + \beta_1 X_{1i} + \ldots + \beta_n X_{ni}) = 0$$

$$Y_i - \beta_0 - \beta_1 X_{1i} - \ldots - \beta_n X_{ni} = 0 \tag{13}$$

Furthermore, we are concerned with absolute differences, so we disregarded negative signs by squaring the difference. Lastly, to ensure the appropriate beta values are found, sum the differences of the entire range of (X_i,Y_i) so as to minimize the overall squares.

$$Q=\sum_{i=1}^{n}(Y_i-\beta_0-\beta_1X_{1i}-...-\beta_nX_{ni})^2 \tag{14}$$

OLS does not find the exact β_k (k=$0...n$) values, but rather estimates, b_0, $b_1,...,b_k$ that minimize the criterion Q for every (X_i,Y_i) pair. OLS is completed systematically using computer software. We can derive β estimates from equation (14) using calculus, differentiating with respect to each value of β.

$$\frac{\partial Q}{\partial \beta_0}=-2\sum_{i=1}^{n}(Y_i-\beta_0-\beta_1X_{1i}-...-\beta_nX_{ni}) \tag{15}$$

Substituting b_k in for β and set equal to zero, we get

$$-2\sum_{i=1}^{n}(Y_i-b_0-b_1X_{1i}-...-b_nX_{ni})=0 \tag{16a}$$

and, after simplifying,

$$\sum_{i=1}^{n}(Y_i-b_0-b_1X_{1i}-...-b_nX_{ni})=0 \tag{16b}$$

$$\sum_{i=1}^{n}Y_i-\sum_{i=1}^{n}b_0-\sum_{i=1}^{n}b_1X_{1i}-...-\sum_{i=1}^{n}b_nX_{ni}=0 \tag{16c}$$

$$\sum_{i=1}^{n}Y_i-nb_0-b_1\sum_{i=1}^{n}X_{1i}-...-b_n\sum_{i=1}^{n}X_{ni}=0$$

$$\sum_{i=1}^{n}Y_i=nb_0+b_1\sum_{i=1}^{n}X_{1i}+...+b_n\sum_{i=1}^{n}X_{ni} \tag{16d}$$

Equation (16d) made up one part of the normal equations. The form is unique for the first point estimate, b_0. For the second (and following) normal equations, we consider the remaining point estimates (b_1,…, b_n)

$$\begin{array}{ll}\dfrac{\partial Q}{\partial b_1}=-2\displaystyle\sum_{i=1}^{n}X_{1i}(Y_i-b_0-b_1X_{1i}-...-b_nX_{ni}) \\ \vdots \qquad\qquad\qquad \vdots\end{array} \tag{17a}$$

$$-2\sum_{i=1}^{n} X_{1i}(Y_i - b_0 - b_1 X_{1i} - \ldots - b_n X_{ni}) = 0$$

$$\vdots \qquad\qquad\qquad \vdots \tag{17b}$$

and, after simplifying becomes

$$\sum_{i=1}^{n} X_{1i}Y_i - \sum_{i=1}^{n} b_0 X_{1i} - \sum_{i=1}^{n} b_1 X_{1i}{}^2 - \ldots - \sum_{i=1}^{n} b_n X_{ni} X_{1i} = 0 \tag{17c}$$

$$\sum_{i=1}^{n} X_{1i}Y_i - b_0 \sum_{i=1}^{n} X_{1i} - b_1 \sum_{i=1}^{n} X_{1i}{}^2 - \ldots - b_n \sum_{i=1}^{n} X_{ni} X_{1i} = 0$$

$$\sum_{i=1}^{n} X_{1i}Y_i = b_0 \sum_{i=1}^{n} X_{1i} + b_1 \sum_{i=1}^{n} X_{1i}{}^2 + \ldots + b_n \sum_{i=1}^{n} X_{ni} X_{1i} \tag{17d}$$

Equation (17d) is the second normal equation. We express the normal equations in matrix notation as follows:

$$\begin{bmatrix} \sum_{i=1}^{n} Y_i \\ \sum_{i=1}^{n} X_{1i}Y_i \\ \vdots \\ \sum_{i=1}^{n} X_{ni}Y_i \end{bmatrix} = \begin{bmatrix} nb_0 + & b_1 \sum X_{1i} + \ldots & + b_n \sum X_{ni} \\ b_0 \sum X_{1i} & b_1 \sum X_{1i}{}^2 + \ldots & + b_n \sum X_{ni} X_{1i} \end{bmatrix} \tag{18a}$$

Equation (18a) becomes

$$\begin{bmatrix} \sum_{i=1}^{n} Y_i \\ \sum_{i=1}^{n} X_{1i}Y_i \\ \vdots \\ \sum_{i=1}^{n} X_{ni}Y_i \end{bmatrix} = \begin{bmatrix} n & \sum X_{1i} \ \ldots & \sum X_{ni} \\ X_{1i} & \sum X_{1i}{}^2 \ldots & \sum X_{ni} X_{1i} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix} \tag{18b}$$

or, equivalently

X'Y = X'X **b** (19)

where $\mathbf{b}$ is the vector of least squares regression coefficients, $b_0 \ldots b_n$. To obtain the estimates for the regression coefficients, we use matrix multiplication on equation (19).

$$X'Y = X'X\,\mathbf{b}$$

$$(X'X)^{-1}\,X'Y = (X'X)^{-1}\,X'X\,\mathbf{b}$$

Since $(X'X)^{-1}\,X'X = \mathrm{I}$ and $\mathrm{I}\mathbf{b} = \mathbf{b}$:

$$(X'X)^{-1}\,X'Y = \mathbf{b} \tag{20}$$

A final step of this phase is to use the estimated regression coefficients (b_k) to find the estimate of the regression function ($\hat{Y}_i$, "Y-hat"). This process results in what statisticians call the "fitted model." The fitted model is no more than the original model with the substituted beta estimates (b_k). Before this is accomplished, we summarize:

(a) Original regression model form:

$$Y_i = E[Y_i] + \varepsilon_i \tag{21a}$$

where , in general

$$E[Y_i] = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_n X_{ni}\,. \tag{21b}$$

(b) After obtaining estimates for β_k, equation (20), the fitted regression model form is:

$$\hat{Y}_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots + b_n X_{ni} \tag{22}$$

(c) In order to obtain a specific value ($\hat{Y}_i$) of the estimated regression function at the level X_i of the predictor variable, a substitution of b_k's into equation (22) is made. Equation (22) will not give us a perfect fit, but will get us as close as we can to the actual value, given the power of our predictors. The difference between the original Y and its estimate, Y-hat, is the subject of the next section

C. ERROR TERMS AND RESIDUALS

Until now, we have not discussed the error term, epsilon (ε_i). Using equation (19), we define the general error of the model as:

$$\varepsilon_i = Y_i - E[Y_i] \tag{23}$$

Equation (23) implies that we must know the true (expected) value, but the true value is unknown. However, we know the value of its estimate, namely, the fitted value ($\hat{Y}_i$). We substitute the estimate for the expected value and find the deviation. This difference is termed "residual" (e_i) and defined as:

$$e_i = Y_i - \hat{Y}_i \tag{24}$$

Residuals help determine the appropriateness of a particular regression model. Earlier, we forced the residual to be zero in developing the normal equations. This ensured we were able to find estimated values of the regression coefficients that minimized the sum of squares. Another form of equation (14) is:

$$Q = \sum_{i=1}^{n} \left(Y_i - E[Y_i]\right)^2 = \sum_{i=1}^{n} \left(\varepsilon\right)^2 = 0, \tag{25a}$$

When Y-hat is substituted in for $E[Y_i]$ and e_i is substituted for for ε_i, we get:

$$\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 = \sum_{i=1}^{n} \left(e_i\right)^2 = SSE \tag{25b}$$

This is the same thing as saying:

$$\sum_{i=1}^{n} \left(e_i\right)^2 = 0$$

The calculation found in equation (25a and 25b) yields the error (or "residual") sum of squares. Realistically, the error terms vary in for each (X_i, Yi) pair. The goal is to ascertain the amount of variability closer to zero. In order to get an idea of the variability of the probability distribution of Y, we must estimate the average variance of the error terms, σ^2. Much like E[Y], σ^2 is unknown but we can obtain its unbiased estimator using the error sum of squares (SSE) (equation 25b) and dividing by the degrees of freedom (*n-2*). We call this estimator the mean square error (MSE).

$$s^2 = \frac{SSE}{n-2} = \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{n-2} = \frac{\sum_{i=1}^{n}\left(e_i\right)^2}{n-2} = MSE \tag{26}$$

At times, we are interested in the deviation of the response (Y_i) from the average ($\bar{Y}$, "Y-bar"). We further defined this as the measure of uncertainty in predicting the outcome after accounting for the predictors. Similar to equation (24), we calculate it using sum of squares and called the sum of squares total (SSTO).

$$\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2 = SSTO \tag{27}$$

Notice, SSTO and SSE help us find the formula for measuring the variability of the Y_i associated with the regression line without taking into account any predictor variables. We call this sum of squares regression (SSR) and use the following formula:

$$\begin{aligned} SSR = {} & SSTO - SSE \\ = {} & \sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2 - \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \\ = {} & \sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2 \end{aligned} \tag{28}$$

Finally, we use SSTO, SSE, and SSR to measure the effect of *X* in reducing the variation in *Y* when expressed as a ratio, called R-squared.

D. MODEL COMPARISON USING R^2

SLR analysis provided an initial basis to compare models called the R^2 (R-squared) or the coefficient of multiple determination. We interpret R^2 as the proportion of variation in the response (*Y*) explained by use of the set of variables

$X_1, \ldots, X_{p-1}$, p= (number of parameters). R^2 falls between zero and one, assuming the value 0 when all b_k= 0 and the value 1 when all Y observations fall directly on the fitted regression surface (e=0). We represent R^2 as:

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO} \tag{29a}$$

In the event we add more variables to our model, we will experience an increase in SSR and SSE, thus increasing our R^2. However, to avoid erroneous inflation of the coefficient of multiple determinations by adding more variables, most statistical textbooks recommend using an adjusted R^2 or "R^2_a". We calculate R-squared-adjusted by dividing each sum of squares by its associated degrees of freedom as follows.

$$R_a^2 = 1 - \frac{\dfrac{SSE}{n-p}}{\dfrac{SSTO}{n-1}} = 1 - \left(\frac{n-1}{n-p}\right)\frac{SSE}{SSTO} \tag{29b}$$

E. INFLUENCE OF VARIABLES IN THE PRESENCE OF OTHERS

Multiple variables may describe the same characteristic or influence in a response, often without the researcher initially knowing it. It is possible the redundancy of two or more predictors do more harm than good by inefficiently assigning variance in the response. Regression analysis defines multicollinearity as correlation between predictor variables. Several effects of multicollinearity are variation in estimated regression coefficients as sample populations change and unsatisfactory regression fit. In addition, a lower R^2 may occur as two or more predictor variables relate to each other.

Pairwise coefficients of simple correlation or Variance Inflation Factors (VIF) help diagnose multicollinearity. We calculate VIF using the following formula:

$$(VIF)_k = (1 - R_k^2)^{-1},\ k = 1, 2, \ldots, p-1 \tag{30}$$

APPENDIX F. LOGISTIC REGRESSION APPROACH EXPLAINED

Note: Mathematical formulation garnered from Montgomery, Peck, & Vining (2001).

Logistic Regression was used when the outcome *Y* was categorical with two possible outcomes, either “1” or “0” (1=“YES,” 0= “NO”, or vice versa). Y_i is considered a Binomial (n_i, π_i) random variable with π_i defined as the probability that Y_i=1 and 1- π_i as the probability that Y_i=0.

$$\begin{aligned} E[Y_i] &= 1\times pr(Y_i=1) + 0\times pr(Y_i=0) \\ &= 1\times \quad (\pi_i) \quad + 0\times \quad (1-\pi_i) \\ &= \pi_i \end{aligned} \tag{31}$$

The linear predictor (η_i) of the expected value (π_i) takes the form

$$\eta_i = \beta_0 + \beta_1 X_{1i} + ... + \beta_n X_{ni} \tag{32a}$$

We use the following transformation to link π_i to the linear predictor η_i.

Logistic Link Function:

$$g(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) = \eta \tag{32b}$$

We solved π_i using algebra to get

$$\pi_i = \frac{\exp(\beta_0 + \beta_1 X_1 + ... + \beta_{p-1} X_{p-1})}{1+\exp(\beta_0 + \beta_1 X_1 + ... + \beta_{p-1} X_{p-1})} = \frac{\exp(\eta_i)}{1+\exp(\eta_i)} \tag{33a}$$

Equation (33a) has the same form as the logistic cumulative distribution function. The logistic distribution is very similar to the normal distribution and has the nice properties of mean equal to zero and standard deviation σ = π/√3.

We use the method of maximum likelihood to estimate the regression coefficients, denoted $\hat{\beta}$ (“Beta-hat”). These values, found oftentimes through numerical techniques or iteratively reweighted least squares, may then be substituted into equation (33a) and reveal the following fitted logistic regression model:

$$\hat{\pi}_i = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 X_1 + ... + \hat{\beta}_{p-1} X_{p-1})}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 X_1 + ... + \hat{\beta}_{p-1} X_{p-1})} = \frac{\exp(\hat{\eta}_i)}{1 + \exp(\hat{\eta}_i)} = \hat{Y}_i \tag{33b}$$

To summarize, we started with the link function, equation (32), used the maximum likelihood estimators ("$\hat{\beta}$") and substituted the result into equation (33). For given values of the predictor(s) X_i, we estimated the probability of the response π_i. If that probability is close to "1," we associated the response with a "YES," and if the probability is closer to "0" than it is to "1," then we associated the response with "NO."

APPENDIX G. “R” COMPUTER CODE AND PLOTS

A. LINEAR MODEL R CODE

```
HP4=read.csv(file.choose())
HP4cor1=data.frame(HP4[c(9,10,11,12,13,14,15,22)])
cor(HP4cor1)
cor(HP4$recath2,HP4$playedsport1)
        #.86 correlation between the two. confirm with model matrix below

h4=HP4[-c(1,2,3,9,12)]      #take out cols 1:3, WCS and CLS

#LM1
h.lm1=lm(hrdns2~.,data=h4)
hcor2=cor(model.matrix(h.lm1))
diag(hcor2)=0
which(hcor2>abs(.5))
hcor2[282];hcor2[315]       #confirmed cor btwn recath and playedsport

#update data frame minus recath
h4.new=HP4[-c(1,2,3,7,9,12)]
h.lm2=lm(hrdns2~.,data=h4.new)
summary(h.lm1)
summary(h.lm2)

#stepwise with h.lm2
h.step1=step(h.lm2,direction="both",trace=FALSE)
summary(h.step1)

#Plot of [possibly] most sig predictors
pairs(~hrdns2+ceer+pae+eas+aas+fas+gender+playedsport1+m.degree+typehs
,data=h4.new,cex.labels=2)

#interactions
h.lm3=lm(hrdns2~.^2,data=h4.new); summary(h.lm3)
h.step2=step(h.lm2,scope=~.^2,direction="both",trace=FALSE);
summary(h.step2)

#ANOVA between stepwise models
anova(h.step1,h.step2,test="Chi")

#correlations
hcor3=cor(model.matrix(h.step2))
```

```
diag(hcor3)=0
corstr=c(which(hcor3>abs(.5)))
uni=unique(hcor3[corstr])

# diagnostics
par(mfrow=c(2,2))
plot(h.lm2)
plot(h.step2,cex.labels=2)

#Kruskal Wallis
kruskal.test(hrdns2~gender,data=h4.new)
kruskal.test(hrdns2~playedsport1,data=h4.new)
kruskal.test(hrdns2~typehs,data=h4.new)
kruskal.test(hrdns2~f.degree,data=h4.new)
names(kruskal.test(hrdns2~m.degree,data=h4.new))

#explore gender
plot(h4.new$gender,h4.new$hrdns2,ylab="Total Hardiness")
title(main="Gender versus Hardiness",ylab="Total Hardiness")

stripchart(h4.new$hrdns2 ~ h4.new$gender, vertical=TRUE, method="jitter",
 pch=16, col="red",ylab="Total Hardiness")
yhat<-tapply(fitted(h.step2),h4.new$gender,mean)
for(i in 1:length(yhat)){
  lines(c(i-.2,i+.2),rep(yhat[i],2))
  }
title(main="Hardiness by Gender")

#h4.new2=h4.new[-685,]

#hard=table(h4.new$hrd,h4.new$gender)
#cbind (hard, round (100 * hard[,1] / rowSums (hard), 1),round (100 * hard[,2] /
rowSums (hard), 1))

# Tukey Test (anova) for Gender
a1=aov(hrdns2~gender,data=h4.new)
TukeyHSD(a1);plot(TukeyHSD(a1))

#explore typehs
hard2=table(h4.new$hrdns2,h4.new$type)
sum(hard2[,1])

#additional plots of Hardiness by Cat variable
# playedsport1
stripchart(h4.new$hrdns2~h4.new$playedsport1, vertical=TRUE, method="jitter",
```

```
 pch=16, col="red",ylab="Total Hardiness")
yhat<-tapply(fitted(h.step2),h4.new$playedsport1,mean)
for(i in 1:length(yhat)){
  lines(c(i-.2,i+.2),rep(yhat[i],2))
  }
title(main="Hardiness by Varsity Sport Player")

#typehs
stripchart(h4.new$hrdns2 ~ h4.new$typehs, vertical=TRUE, method="jitter",
 pch=16, col="red",ylab="Total Hardiness")
yhat<-tapply(fitted(h.step2),h4.new$typehs,mean)
for(i in 1:length(yhat)){
  lines(c(i-.2,i+.2),rep(yhat[i],2))
  }
title(main="Hardiness by Type of High School")
```

B. LINEAR MODEL PAIRS PLOT OF MOST SIGNIFICANT PREDICTORS

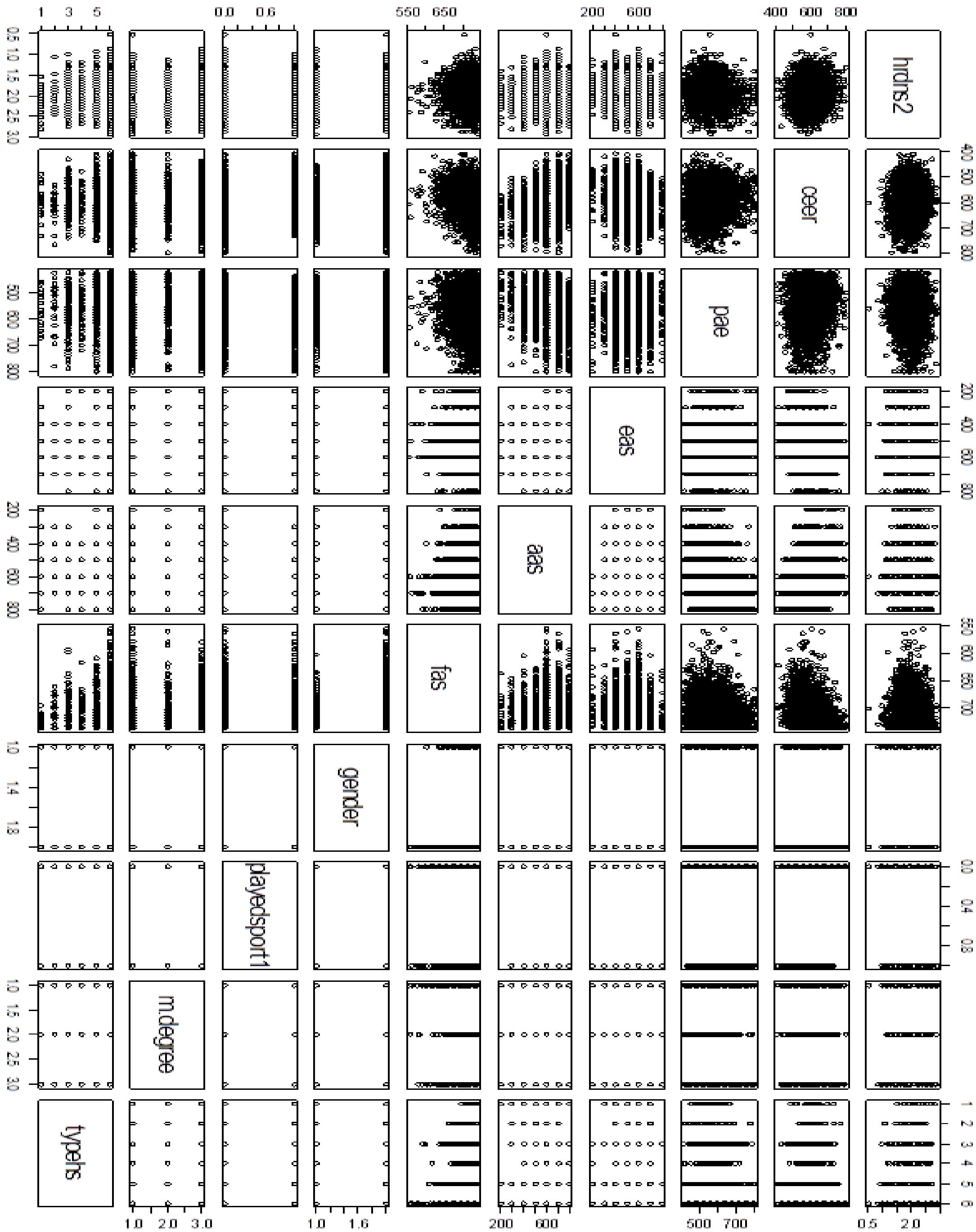

Figure 12. Pairs Plot of Most Significant Predictors of Hardiness

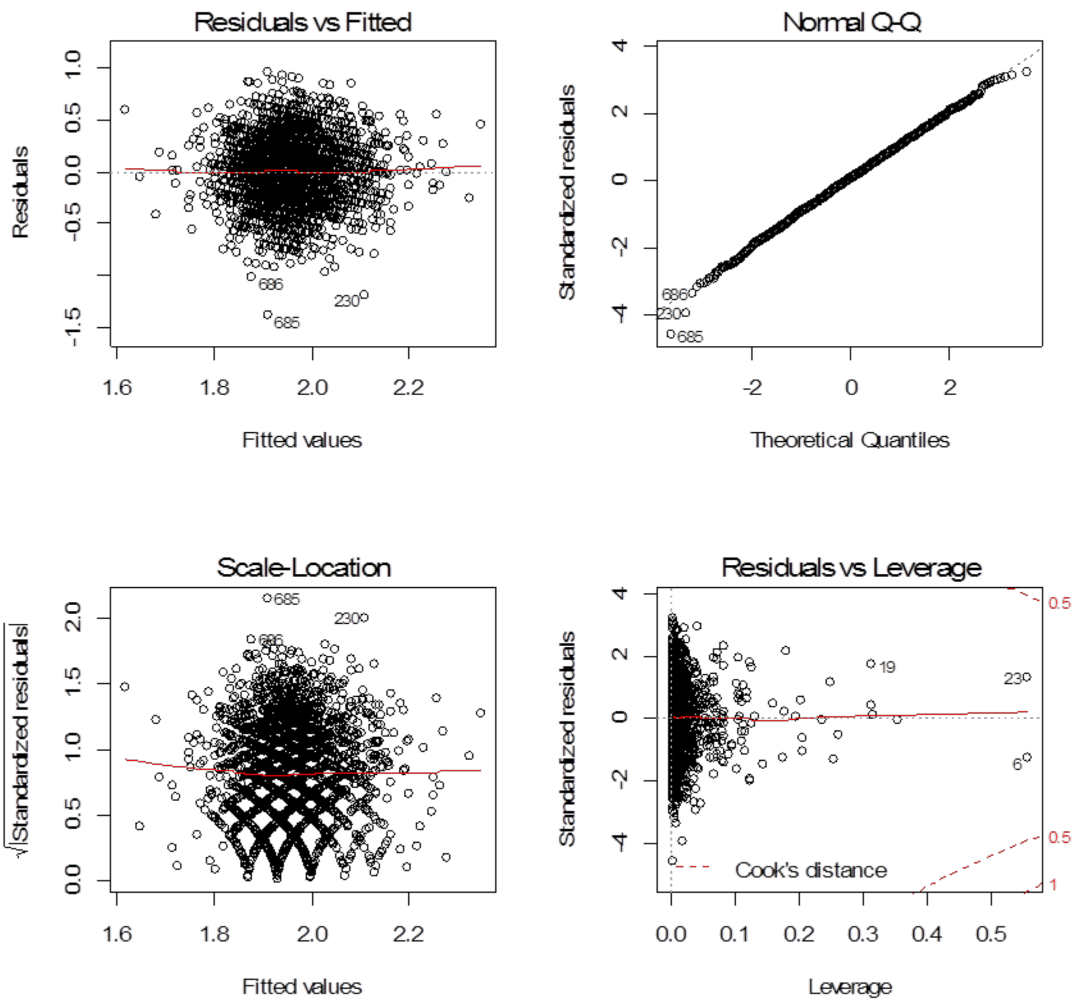

Figure 13. Linear Model Diagnostics

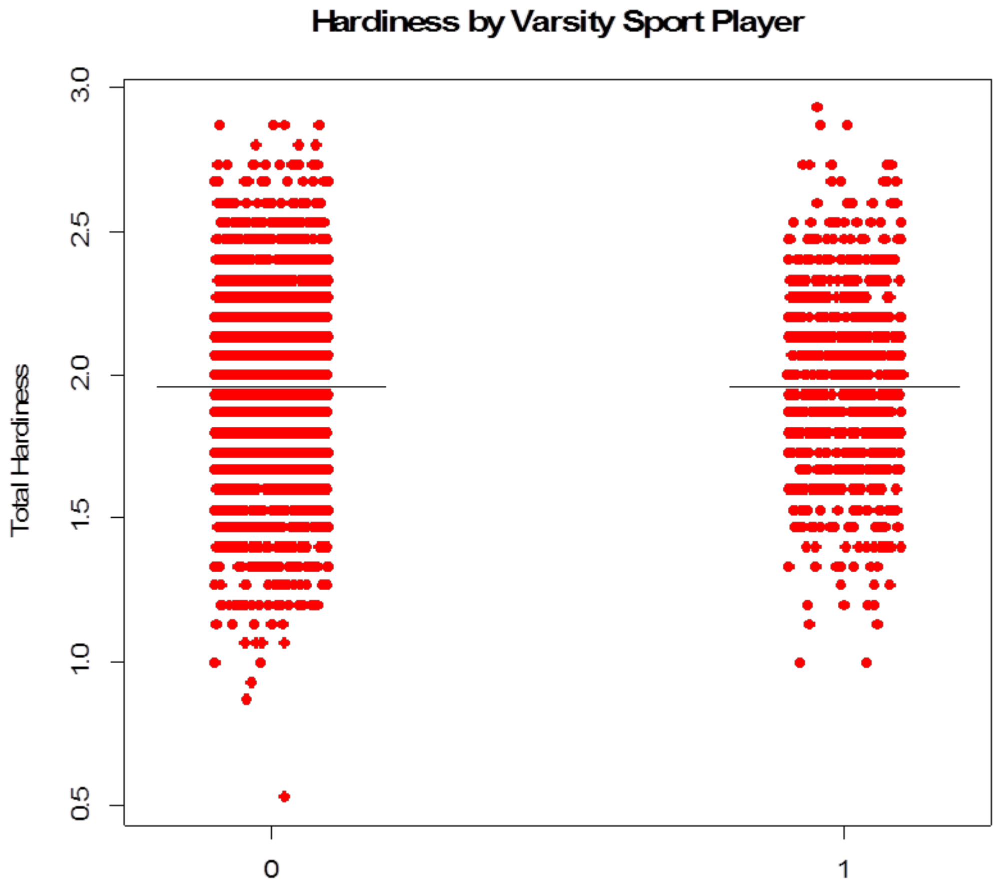

Figure 14. Hardiness versus Intercollegiate Athlete (1="Yes")

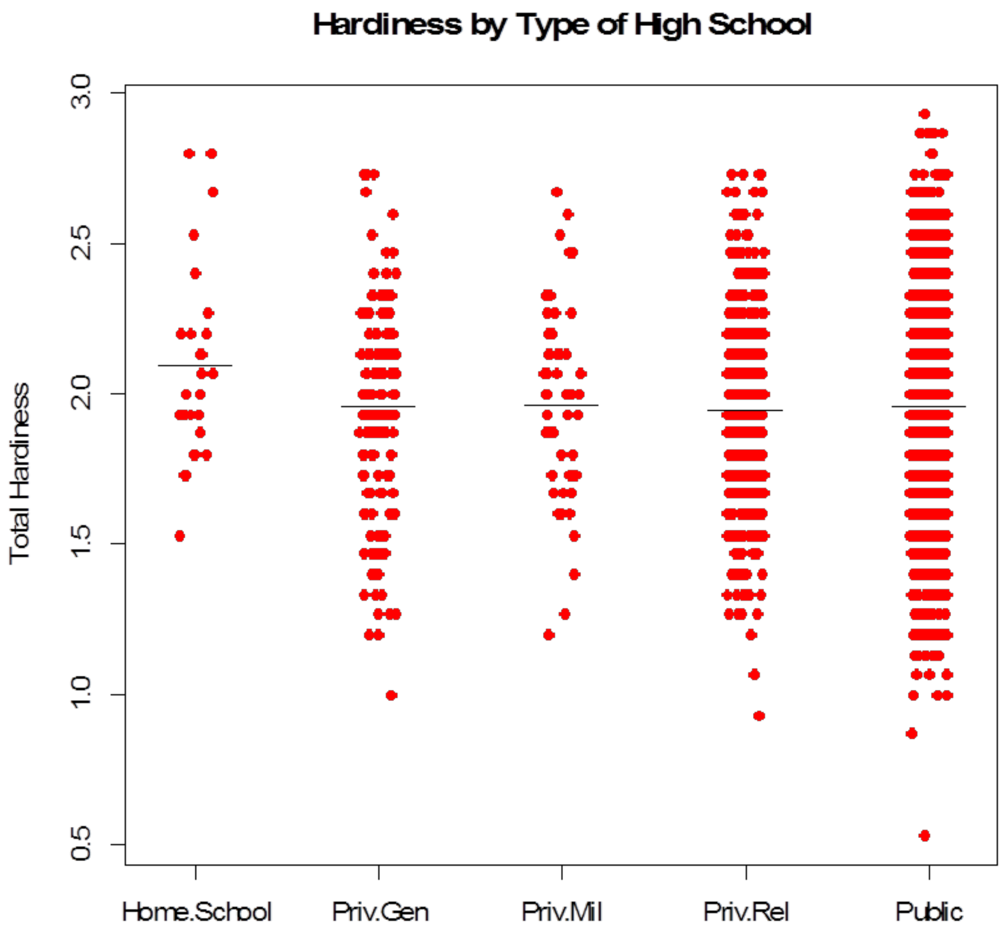

Figure 15. Hardiness versus Type of High School

C. LOGISTIC REGRESSION MODEL R CODE

```
*** RTN #2 *** ACTIVE DUTY VS. LOSS

RTN=read.csv(file.choose())
names(RTN)
rtn=RTN[-c(1,2,3)]
names(rtn)
pairs(status~babr+ceer+pae+eas+aas+fas+m.degree+f.degree+cm2+co2+ch2+a
psc+mpsc+ppsc+typ.ath,data=rtn)

#1. GLM1
rtn.glm1=glm(status~.,family=binomial,data=rtn)
summary(rtn.glm1)
```

```
# ANOVA for glm1 versus step

anova(rtn.glm1,step.rtn1,test="Chi")

#GLM2 clog-log
rtn.glm2=update(rtn.glm1,family=binomial(link="cloglog"))
summary(rtn.glm2)

# ANOVA for logit versus clog-log

anova(step.rtn1,rtn.glm2,test="Chi")
Analysis of Deviance Table

#Model 1: status ~ babr + ceer + pae + eas + aas + fas + m.degree + f.degree +
#    cm2 + co2 + ch2 + apsc + mpsc + ppsc + typ.ath
#Model 2: status ~ babr + ceer + pae + eas + aas + fas + m.degree + f.degree +
#    cm2 + co2 + ch2 + apsc + mpsc + ppsc + typ.ath
#  Resid. Df Resid. Dev Df Deviance
1      1371     1735.9
2      1371     1737.2  0  -1.3125
# first -glm1 (log-log) is best, by (lower) deviance

# stepwise on rtn.glm1
step.rtn1=step(rtn.glm1,trace=FALSE)
summary(step.rtn1) #stepwise glm1 is better than glm1 and glm2 by AIC

# compare stepwise glm1 with glm3-interaction
rtn.glm3=glm(status~.^2,family=binomial,data=rtn)
summary(rtn.glm3)
# generated higher AIC. no good, Proceed with glm1(stepwise)

#2. Use GAM and termplot to determine if transformation of a
# predictor is needed.

library(gam)
rtn.gam1=gam(status~typ.ath+m.degree+f.degree+s(cm2)+s(co2)+s(ch2)
+s(ceer)+s(pae)+s(eas)+s(aas)+s(fas)+s(apsc)+s(mpsc)+s(ppsc)+babr,
family=binomial,data=rtn)

rtn.gam2=gam(status~s(aas)+babr,family=binomial,data=rtn)

par(mfrow=c(2,1))
termplot(rtn.gam2,partial.resid=TRUE,col.res="dark green")

### no transformations needed!!!!
```

#4(a and b). drop1 pvals<.05 are significant and should be kept in model
drop1(step.rtn1,test="Chisq") # confirmed babr IN and aas should be kept in model

#5. Confusion Matrix
##glm1
y<-rtn$status

pi.hat=predict(step.rtn1,type="response")
#head(pi.hat) # these are with old data
#head(pi.hat>.5)

tbl1=table(y, pi.hat>.62) ;tbl1
# y FALSE TRUE
# 0 284 222 # Loss: 112 classified correctly, 394 incorrectly;
# 1 307 590 # Actv: 83 classified incorrectly and 814 classified correctly.
# There are more personnel Active Duty so they are being classified better.

q1=tbl1[1]/sum(tbl1[1],tbl1[3])
q2=tbl1[3]/sum(tbl1[1],tbl1[3])
q3=tbl1[2]/sum(tbl1[2],tbl1[4])
q4=tbl1[4]/sum(tbl1[2],tbl1[4])
ptbl1=data.frame(q1,q2,q3,q4);ptbl1

mtx=matrix(data=ptbl1,nrow=2,ncol=2,byrow=TRUE,dimnames = list(c("0", "1"), c("FALSE", "TRUE"))); mtx
(q1+q4)*100;(q2+q3)*100

.62 Best Class rate!!
FALSE TRUE
0 0.5612648 0.4387352
1 0.3422520 0.657748
[1] 121.9013
[1] 78.09871

##6(a) Misclassification Rate
z=y
z!= (pi.hat>.62) # trues if misclassified, falses if classified correctly
sum(z!= (pi.hat>.62))
# 529 # number of misclassifications
mean(z!= (pi.hat>.62))
# 0.3770492

##7(a). Cross-validation

```
library(boot)
cost<-function(y,pi.hat) mean(y!=(pi.hat>.62))
cv.glm(rtn,step.rtn1,cost,K=10)$delta
# 0.3877406 0.3843210   #our cv estimate
```

D. LOGISTIC REGRESSION MODEL PLOTS

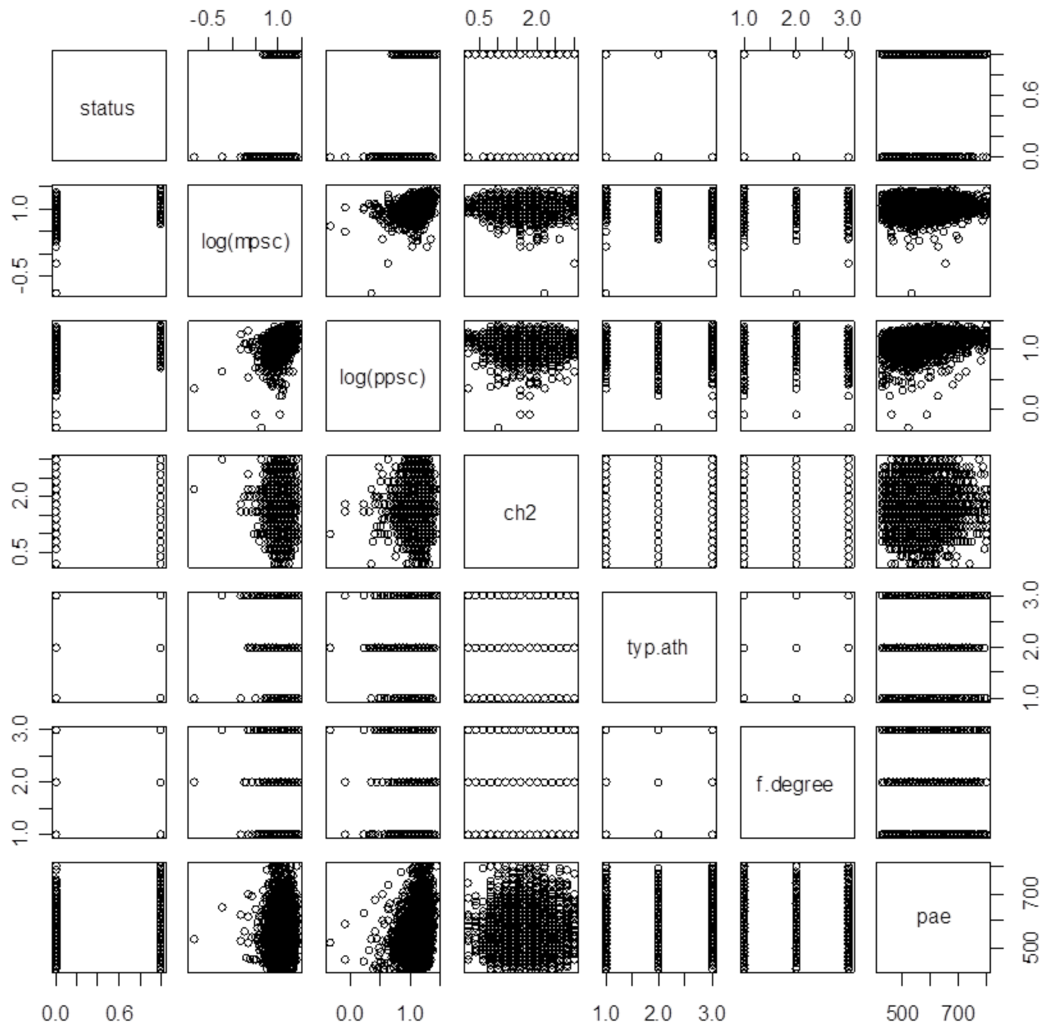

Figure 16. Pairs Plot (Graduation “Status” versus Separation)

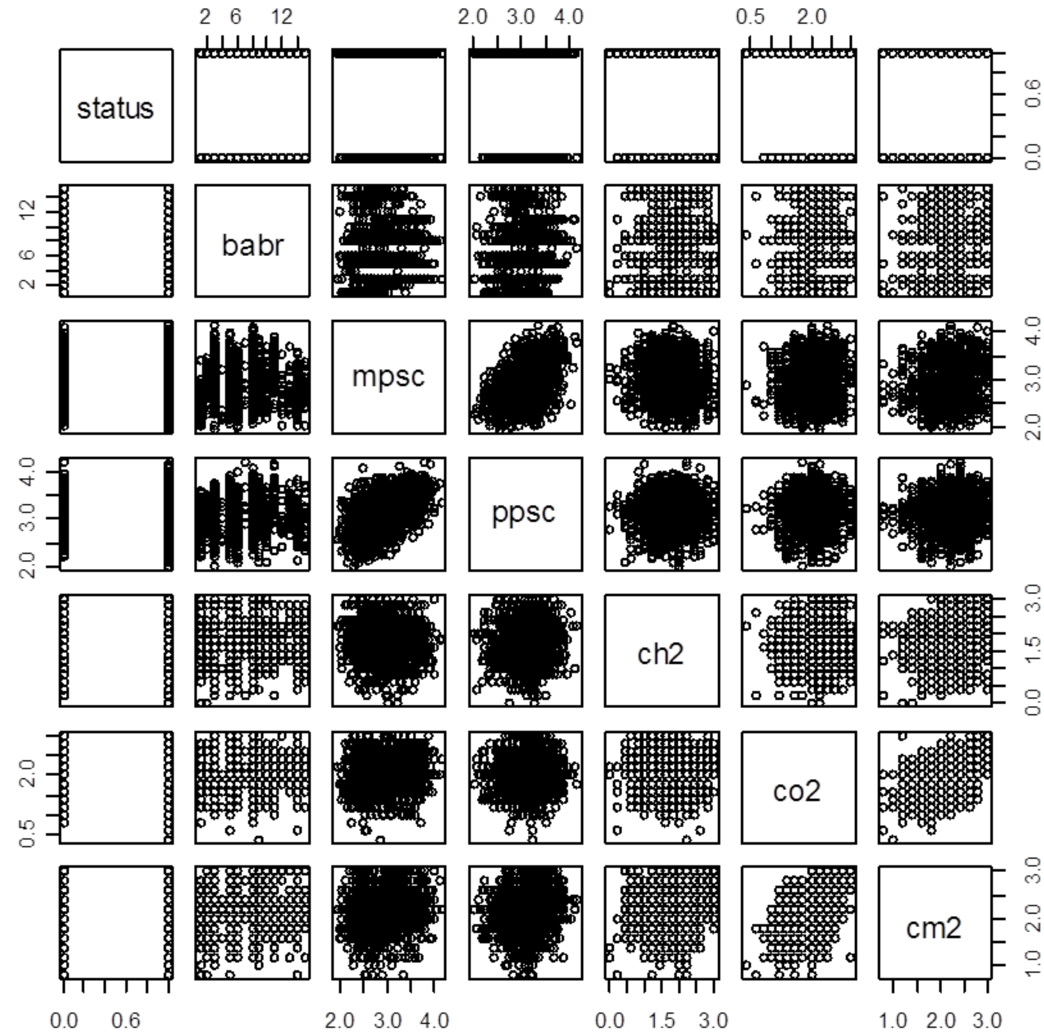

Figure 17. Pairs Plot (Active "Status" versus Loss)

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